

Advancing and Applying Modern Counterfactual Analysis in Public Economics and Policy Analysis

Lindon Scott Belshe
University of Stirling

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Advisors:

Mirko Moro (University of Stirling)
Hector Gutierrez Rufrancos (University of Stirling)
Eion McLaughlin (Heriot-Watt University)
Thiemo Fetzer (University of Warwick)

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Introduction

One popular approach to policy analysis emphasises the construction of counterfactuals as a means of isolating the causal effects of some intervention or treatment – often a policy interventions or broader social changes. These alternative trajectories allow researchers to estimate both short- and long-term impacts of treatments or events across diverse contexts. Yet, because the value of counterfactual analysis depends on the credibility of its underlying construction, growing attention has turned to improving how counterfactuals are modeled and applied. Better counterfactual construction not only strengthens causal inference but also broadens the scope of counterfactual analysis itself; it transforms it from a tool limited to well-defined, date-specific experiments into one capable of evaluating complex, historical, and systemic policy processes.

Traditional empirical methods may encounter difficulties in addressing “what-if” scenarios, especially when interventions are challenging to isolate or change gradually over time. In recent years, alternative approaches to counterfactual construction have been developed to enhance the methodological rigor and applicability of quasi-experimental policy analysis. For example, the synthetic control method and machine learning–based simulation models provide options for estimating counterfactual outcomes with increased reliability and adaptability. The unifying objective of this dissertation is to advance these modern approaches to counterfactual construction for improved policy analysis in public economics, demonstrating how they can yield more credible insights across different domains and can be applied to important but challenging questions. Through three distinct but thematically linked studies, the research showcases how cutting-edge counterfactual techniques enhance our ability to measure policy impacts and inform evidence-based decision-making.

Collectively, the three papers that follow demonstrate the application of these approaches across distinct yet complementary areas of public economics. The first examines long-run health outcomes through the lens of Scotland’s life expectancy divergence, using synthetic control methods to identify when and how its trajectory began to deviate from comparable countries. The second extends this framework to fiscal policy, evaluating the

economic and mortality effects of Ireland’s corporate tax under cutting through a similar but more rigid counterfactual design. The third shifts from retrospective evaluation to prospective simulation, applying machine learning–based valuation and redistribution models to explore revenue-neutral reforms to England’s Council Tax system. Collectively, these studies illustrate how refined counterfactual construction can illuminate complex economic and social processes that lie beyond the reach of conventional empirical tools.

1 A Comparative Analysis of the Scottish Divergence in Life Expectancy at Birth

The first paper, *A Comparative Analysis of the Scottish Divergence in Life Expectancy at Birth*, applies synthetic control analytics within a historical and demographic context. The study aims to explore one of the most enduring puzzles in public health economics, which is Scotland’s persistent lag in life expectancy relative to other Western nations. In the paper, a “synthetic Scotland” is constructed from a weighted combination of comparable countries and covariates to estimate what Scotland’s life expectancy trajectory might have been in the absence of its observed divergence. This counterfactual framework allows for an exploration and reassessment of when Scotland’s mortality path began to deviate, tracing long-run trends across well over a century of data. The findings reveal that Scotland’s life expectancy deficit likely emerged in two waves, with the first occurring shortly after World War I. This is far earlier than the previously assumed mid-century period. The initial divergence set in motion a slower rate of health improvement that persisted through the 20th century. The analysis also confirms a secondary divergence during the 1970s and 1980s, coinciding with economic and social restructuring across the UK. The second wave is more in-line with prior theories.

Beyond identifying the timing of these breaks, the study disaggregates results by age and sex, finding that younger working-age populations have long accounted for the greatest burden of excess mortality (and thus shorter life expectancies). Additionally, while male life expectancy has remained comparatively stable in its deficit relative to other countries, the female gap has widened since the 1970s. By applying the synthetic control

framework to contexts without discrete policy interventions, it is demonstrated that counterfactual analysis can serve as a robust exploratory tool to identify latent structural changes beyond simply assessing known treatments. This methodological advancement enhances our understanding of Scotland's public health trajectory and illustrates how constructing credible long-term counterfactuals can provide valuable insights into historical developments influencing current health inequalities.

2 Death and Taxes: Does Corporate Tax Undercutting Result in Lower Economic Growth and Lower Mortality?

The second paper, *Death and Taxes: Does Corporate Tax Undercutting Result in Lower Economic Growth and Lower Mortality?*, extends the counterfactual framework from demographic trends to fiscal tax policy, examining the Republic of Ireland's dramatic corporate tax reductions as a natural experiment in economic and social development. Between 1997 and 2003, Ireland reduced its statutory corporate tax rate from 36% to 12.5%, creating one of the most competitive tax environments in the OECD. Using the SCM, a "synthetic Ireland" is constructed, which represents the country's potential trajectory devoid of these tax reductions. This framework enables a comparative analysis of both macroeconomic and public health outcomes, focusing on foreign direct investment (FDI) per capita, gross national income (GNI) adjusted for purchasing power parity, and mortality rates. The analysis indicates that Ireland's corporate tax policies, which involved significant reductions compared to marginal rate changes elsewhere, were associated with increases in FDI and GNI, as well as enhanced competitiveness and economic activity relative to previous trends in tax rates and trade liberalization. However, it is difficult to isolate the impact of corporate tax measures from broader social and economic developments in the late 1990s and early 2000s. The period known as the Celtic Tiger included multiple factors such as EU integration, educational improvements, and technological growth, which make direct attribution complex. Still, the evidence suggests that substantial tax reductions played a role in Ireland's rapid economic expansion.

The analysis also explores associated health outcomes, with results that are more uncertain but nonetheless suggestive. Improvements in mortality relative to the synthetic counterfactual appear to follow the period of accelerated economic growth, though these effects are subject to lags and noise in the data. The evidence tentatively points to a link between economic gains and better population health, and Ireland's current international standing in mortality rates supports this possibility. Taken together, these findings highlight both the power and the nuance of counterfactual policy analysis. While complete causal separation is rarely attainable in such dynamic historical contexts, the construction of robust counterfactuals allows researchers to draw meaningful and credible inferences about how large-scale fiscal shifts can influence broader social and health outcomes.

By integrating mortality considerations into fiscal policy evaluation, this study expands counterfactual analysis to encompass welfare effects beyond traditional economic metrics. This approach constitutes an innovative synthesis of public finance and health economics within a cohesive empirical framework. Additionally, the paper illustrates that the synthetic control method is effective not only for assessing the direct causal impact of policies but also for identifying secondary effects, such as changes in life expectancy or mortality rates. Ultimately, the research underscores the capacity of counterfactual analysis to connect microeconomic and macroeconomic perspectives, thereby enhancing our understanding of how structural policy decisions shape outcomes in both economic and human development.

3 Reforming Council Tax in England: Empirical Evidence and Reform Options for a Fairer Property Tax System

The third paper, *Reforming Council Tax in England: Empirical Evidence and Reform Options for a Fairer Property Tax System*, turns from retrospective policy evaluation to forward-looking simulation. It develops a data-driven framework to assess how England's property tax system, which is currently anchored to 1991 valuations and relies on a rigid and regressive banding structure, could be modernised to improve both equity and efficiency.

In the study, a comprehensive property-level dataset is constructed using administrative records on property characteristics, historical transactions, and tax liabilities. A geographically weighted Random Forest-based Automated Valuation Model (AVM) is then constructed to estimate contemporary property values. Using these updated valuations, simple revaluation benchmarks and thirteen counterfactual tax system simulations are constructed. These range from modestly adjusting the existing bands to significantly reweighting tax liabilities to even more ambitious structural changes, such as value-based mill levies. Each scenario is evaluated under a revenue-neutral constraint, ensuring comparability to the current system while isolating the effects of valuation updates and structural design choices.

The findings reveal a deeply misaligned tax base, where more than half of dwellings are estimated to fall into inappropriate bands when rank-ordered nationally. This far exceeds other estimates that focus on more local revaluations. This finding implies that high-value properties are systematically undertaxed and lower-value homes are overtaxed. Thus, a simple statistical revaluation alone corrects much of this imbalance, improving horizontal equity by aligning liabilities more closely with market values. However, additional gains arise from introducing finer banding or proportional rate structures, which enhance progressivity and reduce effective tax disparities across regions and income groups.

Beyond the empirical findings, this study contributes methodologically by combining machine learning-based valuation with counterfactual policy simulation. It establishes a framework for evaluating property tax reforms at a national level that is both flexible and reproducible. The model allows policymakers to examine potential outcomes of various design choices prior to implementation, providing quantifiable comparisons regarding simplicity, fairness, and fiscal stability. While the paper does not recommend a single system, it presents evidence that periodic revaluation and incremental structural adjustments could impact fairness in local taxation. Overall, the study demonstrates how computational methods can be applied to policy evaluation, facilitating the analysis of reform concepts through testable policy scenarios.

Collectively, these studies show that counterfactual methods in public economics are advancing in both technique and application. As new data sources and computational tools expand the precision and scalability of such models, the potential for counterfactual measurement to inform real-world policy decisions will only grow. Future innovations, whether through integrating causal inference techniques with machine learning or developing more dynamic forms of synthetic control, will further enhance the capacity of researchers and policymakers to evaluate interventions in complex, interdependent systems. In this sense, the work presented here not only demonstrates current applications but also points toward a rapidly maturing frontier in the quantitative evaluation of public policy.

A Comparative Analysis of the Scottish Divergence in Life Expectancy

Abstract

The public health crisis plaguing Scotland is well established. With a consistently higher mortality rate and shorter life expectancy at birth (LEB) than most other countries in the western world, many studies have attempted to determine the factors that contribute to such health disparities. In addition to socio-economic status, specific health conditions, public policy, lifestyles and environmental factors have all been hypothesised. Still, relatively few studies have focused on long-run trends or sought to identify when Scotland's LEB diverged from similar countries. In this paper, the long-term trends in LEB are analysed in detail to better understand when Scotland's life expectancy diverged from similar nation states. Using the Synthetic Control Method, Scotland's life expectancy trajectory is compared against plausible counterfactual paths, allowing the magnitude and timing of divergence to be quantified and helping to narrow the range of historically plausible explanations. This analysis is performed on age- and sex-specific groups, as well on the aggregates.

The findings imply that the life expectancy deficit first originated shortly after WWI - much earlier than is currently acknowledged. Though middling in terms of ranking at the turn of the century, Scotland didn't keep pace with accelerated growth rates in the west and was soon on a trajectory to have a long-term LEB deficit of about 3.1 years. One key observation is that Scotland failed to capitalize on the lifespan gains resulting from post-WWI reconstruction and investment. The models do, however, confirm the presence of a second divergence between 1970 - 1980. Additionally, the results imply that, while all ages and genders experience lower LEB in Scotland, it is mostly the younger working ages that have long been most effected. The female deficit has also widened since the 1970s, while the male deficit has remained relatively stable.

1 Introduction

For most of the western world, lifespans have been improving for many decades (Floud, et al., 2011). Increases in GDP, advances in medical care, improved disease identification and epidemic detection, and robust environmental, labor and healthcare policies have contributed to lower mortality rates. The Preston curve, which depicts the logarithmic relationship between life expectancy and GDP per capita, has continued to shift upwards, as countries have steadily improved their position along the curve (Preston, 1975).

Scotland has followed a similar overall trend, but life expectancy has consistently lagged behind that of comparable nations in Western Europe, North America and even within the United Kingdom. The most recent data confirms how stark that lag has become. Between 2021 and 2023, life expectancy at birth in Scotland stood at 76.5 years for males and 80.7 years for females, compared to 78.6 and 82.6 respectively across the UK (NRS, 2024). The difference in life expectancy between Scotland and other high-income countries is most evident in urban areas, particularly Glasgow (Reid, 2011; Walsh, et al., 2010; Walsh, et al., 2016). Recent data confirms that Glasgow continues to have the lowest life expectancy of any local authority in Scotland, with male and female life expectancy at 73.6 years and 78.3 years respectively (NRS, 2024).

While many studies have focused on relatively recent explanatory factors contributing to increasing public health deficit, few have focused on when the divergence first began. While some have observed that the life expectancy gap may have originated prior, most research targets the increasingly evident disparity throughout the 1970s and 1980s (McCartney et al. 2019; McCartney et al., 2012; Hanlon et al., 2006; Leyland et al., 2007). Although explanatory factors may be considered independently of the divergence's origin, determining when the gap initially arose offers valuable context for interpreting these factors. This approach aids in distinguishing underlying drivers from historical confounders that may have later contributed to Scotland's life expectancy deficit.

This paper revisits the phenomenon of the “Scottish Divergence.” Its aim is to clarify the timing of this deviation by analysing long-term trends and rigorously constructing counterfactuals up to the year 2017. The analysis concludes at 2017 to avoid the confounding impact of short-term fluctuations introduced by the COVID-19 pandemic. Notably, the paper presents a novel approach for developing long-run counterfactuals or projections, drawing on methodologies from the Synthetic Control Method (SCM) commonly applied in program evaluation (see, e.g. Abadie et al. 2010 and Abadie 2020).

The paper starts with a descriptive analysis of long-term trends, examining and visually comparing life expectancy in Scotland with selected Western countries, mainly those in Western Europe, and their weighted average from 1860 to 2017. These comparisons suggest that Scotland’s life expectancy at birth (LEB) potentially began to separate from the European weighted average around WWI and a significant gap emerged following the conflict. In the interwar period, Scottish LEB was lower than that of England and Wales in every year following 1918.. Following WWI, life expectancies grow quickly for many countries and by the 1930s, a stable lifespan deficit is observable. There is a similar trend present in Scotland, but with more muted impacts. While, at an aggregate level, the country’s LEB was lower than that of England, France, and others, the post WWI recovery was also slower. During World War II, life expectancy again decreased but experienced a swift recovery upon its conclusion. Post-WWII recovery continued, defined as increases beyond the normal trend established in prior decades, persisted until the mid-1950s. Scotland again failing to capture the gains during recovery shared by many of their neighbors, and the deficit grew increased from that point onward. By the 1970s, Scotland had fallen to the bottom of the European life expectancy rankings, a position that led to its informal designation as the “Sick Man of Europe.” That position did not emerge suddenly; rather, it was the result of a slower growth in LEB from the 1950s. While our analysis confirms a wealth of literature identifying the 1950s (and sometimes later) as an origin of the life expectancy deficit in Scotland(see, e.g., McCartney et al., 2019), it also shows that the roots of the divergence may lie earlier; the consistently lower gradient of life expectancy growth relative to similar countries can be traced back to the period immediately following WWI and the 1918 influenza epidemic.

In this study, motivated by the descriptive analysis, we examine more systematically whether Scotland's life expectancy diverged from its *potential* trajectory by focusing on specific *breakpoints* in its long-run trend. We apply the SCM, an econometric technique widely used in programme evaluation to estimate the effects of interventions in comparative case studies (Athey and Imbens, 2017). Although our setting does not involve a singularly identifiable treatment or intervention, we adapt the method to construct the counterfactual trajectory of Scotland by estimating a synthetic unit – a weighted combination of comparison countries that closely replicates Scotland's pre-break trajectory - and using its post-break evolution as a counterfactual benchmark. We focus on six such moments since 1900, each corresponding to a shift in the trend of life expectancy. These shifts represent either recoveries, in which life expectancy begins to rise following a period of stagnation or decline, or decelerations, where the rate of improvement slows noticeably. While the SCM is estimated at regular intervals across the full sample period, the discussion focuses on a subset of breakpoints that correspond to the onset of sustained and economically meaningful divergence in Scotland's life expectancy trajectory. This approach shifts the role of SCM from evaluating discrete interventions to systematically detecting when observed trajectories begin to depart from plausible counterfactual paths.

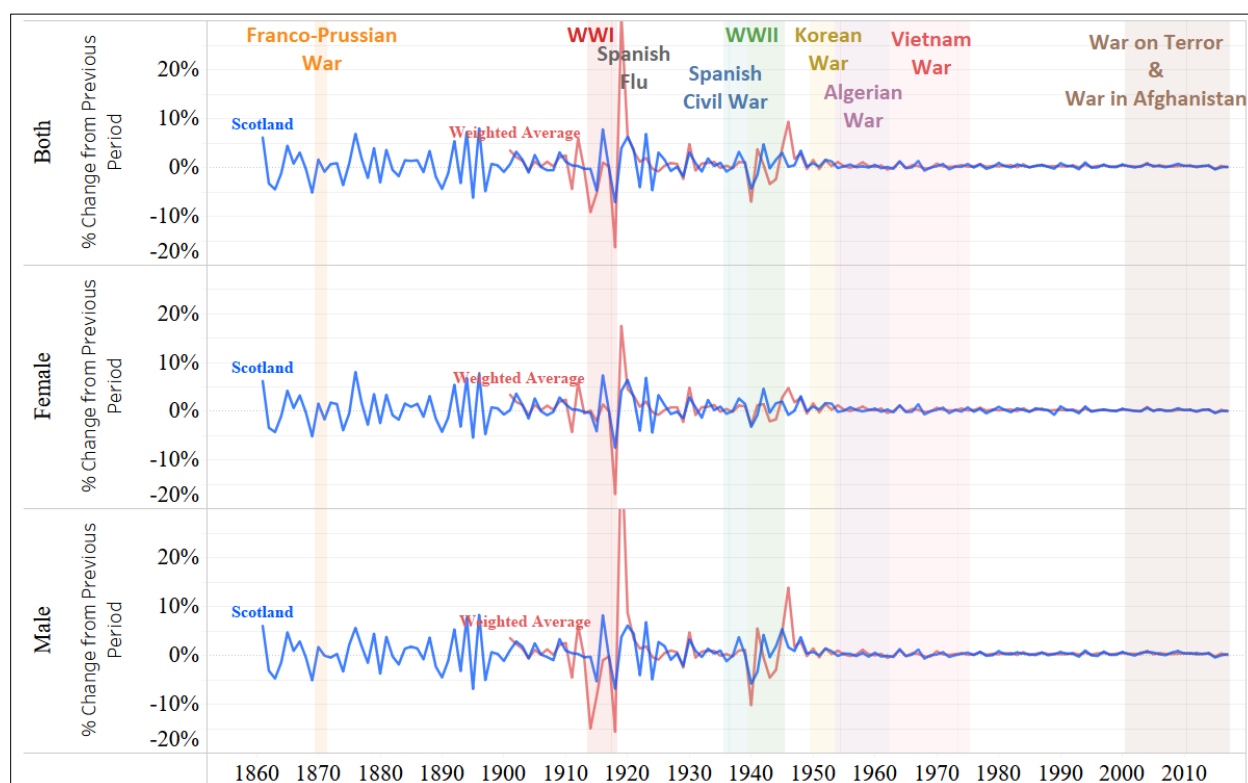
These selected breakpoints are visually striking and include recoveries following major global events that affected most Western countries – namely the aftermaths of WWI (around the year 1919), WWII (around 1946), and a deceleration during the post-war reconstruction period (circa 1955). We also include a recovery at the turn of the 20th century (circa 1900) and two additional trend changes in the early 1970s and 1980s, which are not visually pronounced but have been central to the debate in population health. These are discussed in more detail in Section 2. Finally, for each identified year, we then construct a synthetic Scotland using data from before the trend change. This involves assigning optimal weights to a set of Western European countries by following to create a synthetic comparison group that closely replicates Scotland's trajectory prior to the shift. The calculation of optimal weights is derived from the SCM by Abadie et al. (2014). The post-change trajectory of this synthetic Scotland serves as a counterfactual estimate of what life expectancy might have been had the original trend

continued uninterrupted. The difference between observed and synthetic life expectancy then provides a measure of how Scotland's life expectancy evolved relative to this counterfactual scenario up to 2017.

Confirming the patterns observed in the descriptive analysis, the synthetic control approach suggests that Scotland's divergence from comparable countries may be traced back to the turn of the 20th century and appears to have widened during the interwar period. The 1919 model, which uses data prior to the First World War to construct a synthetic Scotland, estimates a counterfactual life expectancy in 2017 that is approximately 3.15 years higher than the observed value. The 1946 model estimates a value that is much lower, while the 1970 and 1980 confirms that Scotland's LEB diverged from the synthetic Scotland in every year identified.

This paper makes three main contributions. First, it brings together long-run data on life expectancy to document the timing and pattern of Scotland's divergence from comparable countries, using trends beginning as early as 1860. While existing studies have focused primarily on the post-war period, our descriptive analysis suggests that the divergence may have begun earlier. Second, we introduce a counterfactual framework based on the SCM to estimate a more robust benchmark against which to compare Scotland's performance. Rather than relying solely on a country's own historical trajectory, as in models such as Lee-Carter, the approach incorporates information from comparable countries to better account for broader structural and macroeconomic forces common across economies (Lee and Carter, 1992). It also improves upon simple or population-weighted averages by allowing the weights assigned to comparison countries to be determined endogenously, such that the resulting synthetic control closely replicates Scotland's pre-divergence trajectory (Athey and Imbens, 2017). (See Figure 1.1 below for a comparison of Scotland vs the weighted average.)

Figure 1.1: Percentage Change in LEB by Sex compared to Major International Conflicts



Note: This figure shows life expectancy at birth for all countries included in the dataset, plotted from 1860 through 2017. Each line represents a single country, allowing for direct comparison of long-run mortality trends across the full observation period.

In effect, this method provides a disciplined, data-driven counterfactual that supports the analysis without being the primary object of contribution. Third, by tracing the divergence across more than a century of data, the paper provides a clearer empirical basis for interpreting the factors associated with Scotland's mortality disadvantage. Establishing the timing of divergence helps situate potential explanations within their historical context and distinguish early structural drivers from later developments that may have further widened the gap.

The remainder of the paper is structured as follows. Section 2 reviews the broader literature on Scotland's life expectancy divergence. Section 3 describes the data. Section 4 updates the descriptive and trend analysis often found in this literature. Section 5 introduces the Synthetic Control Method to construct counterfactuals for Scotland's life expectancy at selected points in time. Finally, Section 7 concludes and briefly discusses possible extensions.

2 Existing Literature

This section summarises the extensive literature examining trends in life expectancy and mortality rates in Scotland. Broadly, these studies can be classified into two strands. One focuses on comparative trend analysis, while the other seeks to identify underlying determinants. Although the current paper does not focus on the causes of Scotland's performance relative to other countries, we also review studies exploring potential drivers, given their close relevance. In addition to academic research, a number of influential reports have been produced by prominent research institutions looking at both trends and determinants. Among these, the Glasgow Centre for Population Health (GCPH) (a partnership between the University of Glasgow, NHS Greater Glasgow and Clyde, and Glasgow City Council) has published a series of key studies since its founding in 2004 (Glasgow Centre for Population Health, 2021).

2.1 Descriptive and Trend Analysis Studies

Mortality and life expectancy trends have been explored in several studies over many years. Most studies have analysed trends to identify when Scotland began to diverge from other Western countries or to assess more recent changes (Alderson, 1981; Anderson & Roughley, 2018; Riley, 2005). Others have examined cause-specific trends or used historical patterns to forecast life expectancy at birth (LEB) or mortality rates (Li, 2005).

Across studies a broadly consistent picture emerges. Scotland was relatively well positioned in the first half of the 20th century. For both males and females, LEB was of middling rank amongst Western Europe, surpassing France, Spain and Italy. By the 1950s, Scotland's growth rate began to slow down and lag behind most European countries. As a result, Scotland reached one of the lowest ranks by the 1970s. Typically, mortality rates are highest amongst working age individuals; infant mortality is not specifically an outlier relative to other age tranches. The change in rank was fairly uniform for males and females (World Health Organization, 2008; Leon, et al., 2003; Reid, 2008; Minton, et al., 2017).

McCartney et al. (2012) document the same trends and directly address the reputation of Scotland's as the "Sick Man of Europe" since the 1970s, arguing that this status reflects a relatively recent shift rather than a long-standing condition. Using data from the Human Mortality Database (HMD), they compare Scotland to a wide set of countries. The authors agree that, up to approximately 1950, Scotland's life expectancy at birth (LEB) was positioned within the mid-range relative to other regions. From that point onward, Scotland's relative position began to decline, reaching one of the lowest ranks by the 1970s. The authors conclude that Scotland had not always been the "Sick Man of Europe," but that it became one during the second half of the 20th century. They also identify a second stagnation in life expectancy around the early 1980s, shared with the United States and the former USSR, which they attribute to the impact of neoliberal policy reforms. This flattening trajectory persisted into the 1990s and 2000s, with Scotland consistently ranking below its Western European peers and maintaining a position between Western and Eastern Europe by the end of the period (McCartney, et al., 2012). Interestingly, this paper also explores a second flattening in life expectancy around the early 1980s in Scotland, the United States and the former USSR. The data, method and conclusions presented in McCartney et al. (2012) have since been echoed in several other studies. For example, in *Scotland's Populations from the 1850s to Today*, Anderson and Roughley (2018) arrive at similar conclusions after isolating Western European countries using data from the HMD. They also explicitly acknowledge the challenges of analysing long-term life expectancy trends, particularly given that historical events and policy regimes differ across countries. These caveats are clearly noted in their discussion (Anderson & Roughley, 2018).

Sex- and age-specific analyses also confirm Scotland's declining position relative to other Western European countries. Minton et al. (2017) offer a detailed age- and sex-specific analysis of mortality trends in Scotland relative to 19 Western European countries over the period 1950 to 2010. Using data from the Human Mortality Database, they document Scotland's declining rank in life expectancy, with a particular focus on working-age mortality. The analysis highlights excess mortality concentrated in the 15–44 and 45–64 age groups, where Scotland's position is especially weak. While male mortality has historically been higher, the study finds

that the disadvantage is increasingly shared: from the 1990s onward, mortality among younger women has also worsened. This shift contributes to a broader stagnation in life expectancy, suggesting that Scotland's mortality disadvantage – once predominantly male – is now more evenly distributed across sex and age (Minton, et al., 2017).

In their most recent study, Minton et al. (2020) highlight that excess mortality in Scotland and the UK remains high relative to other comparable countries. They also examine much more recent trends in life expectancy and show once again signs of divergence from projections. Using a modified Lee-Carter model, they demonstrate that forecasts (based on data from 1980 to 2011 or from 1990 to 2011) no longer align with life expectancy outcomes in 2018. Their findings point to a new and concerning divergence, one that is recent and sharply defined; this reinforces the view that Scotland's life expectancy slowdown is a recurring but still recent feature rather than a long-standing problem (Minton, et al., 2020; Lee & Carter, 1992).

2.2 Determinants of the Scottish Divergence

The second strand of research that we reviewed explores the determinants of the Scottish Divergence. A wide range of studies have examined potential underlying causes, with some focusing on national-level trends and others on Glasgow specifically, given its particularly poor health outcomes. Much of this literature centres on more recent decades—particularly the period after the 1950s—and identifies a broad set of social, environmental, and behavioural factors that may have contributed to Scotland's persistently lower life expectancy.

Among these factors, socio-economic deprivation is frequently cited as a key driver of Scotland's poor health outcomes. However, its explanatory power appears limited, as studies have shown that even equally deprived cities elsewhere do not suffer the same level of excess mortality seen in Scotland. For instance, Glasgow's deprivation profile is almost identical to that of Liverpool and Manchester, yet premature death rates in Glasgow are over 30% higher (Walsh, et al., 2010). In other words, deprivation alone does not fully explain why health outcomes in Scotland (especially Glasgow) are so much worse – pointing to the influence of

additional, Scotland-specific factors. This has given rise to the terms “Scottish Effect” and “Glasgow Effect”, which refer precisely to this unexplained excess in mortality that cannot be accounted for by deprivation alone. These effects are particularly puzzling because they suggest a population-wide disadvantage: poorer health outcomes are observed across all socioeconomic groups, not just among the most deprived (Carstairs & Morris, 1989, 1991; Hanlon et al., 2006; Reid, 2011; Walsh et al., 2010, 2016; Wrieden et al., 2015; Goodwin, 2016; Botti & Labroo, 2013). In conclusion, while deprivation remains a strong predictor of health inequalities, it does not fully explain why health outcomes in Scotland are systematically worse than in comparable cities such as Manchester or Liverpool in England or Belfast in Northern Ireland (Walsh, et al., 2010; Graham, et al., 2012).

In light of this, some studies explore factors more specific to Scotland or Glasgow. Walsh et al. (2016) and Taulbut et al. (2016) argue that Glasgow’s post-war urban planning decisions, particularly the emphasis on high-rise housing in the city centre, contributed to overcrowding, social dislocation, and long-term public health disadvantages. This stands in contrast to the approaches taken in cities like Manchester and Liverpool, which faced similar pressures from migration and housing demand but responded differently. For example, while Glasgow pursued a massive ‘overspill’ strategy, in which large numbers of (often better-off) residents were relocated to new towns and high-rise estates in the 1960s, Liverpool experienced more internal redevelopment and even pursued some gentrification strategies. This led to poorer populations relocated out of the city (McCartney, et al., 2011). Glasgow’s response resulting in poor housing quality and persistent overcrowding, which remain as significant barriers to improved public health in Glasgow today (Hanlon et al., 2006).¹

¹ In Scotland, greater emphasis was placed on building high-rises in the city centre, with less focus on developing “outer estates.” By 1951, this approach had led to more severe overcrowding in Glasgow. In the decades that followed, underinvestment in housing maintenance and infrastructure exacerbated the problem, prompting more families to move out of the city entirely. As a result, Glasgow’s suburbs became more affluent relative to the city centre, whereas the opposite occurred in parts of northern England. This growing spatial divide contributed to worse health outcomes in Glasgow’s urban core (Taulbut et al., 2016; Walsh et al., 2016).

Scotland’s comparatively poor diet, with higher levels of fat and salt and lower consumption of vegetables and fibre, has also been linked to elevated risks of cardiovascular disease and cancer (Scarborough, et al., 2011; Wrieden, et al., 2015; Gray & Leyland, 2009).² Additional studies point to excess winter mortality, largely driven by inadequate housing and energy poverty (Gemmell et al., 2000), and to elevated exposure to air pollution from coal-based particulates, with long-term impacts on respiratory and all-cause mortality (Beverland et al., 2012; Yap et al., 2012; Hansell et al., 2016).³ The role of sectarianism has also been explored, though comparative analysis finds little evidence of an independent effect once deprivation is accounted for (Walsh et al., 2016; Graham et al., 2012).

More recent work links these accumulated vulnerabilities to the rise of what are now commonly referred to as “deaths of despair” – that is, deaths from suicide, drug overdose, and alcohol-related causes. These trends, first documented in the United States (Case & Deaton, 2015; Case & Deaton, 2020; Ruhm, 2022), have also been observed in Scotland, particularly among working-age white men (Minton et al., 2017; Whyte & Ajetunmobi, 2012; Allik et al., 2020). In general, “deaths of despair” have climbed across the board with greater increases in the more deprived areas (Brown, et al., 2019). Scotland’s historically high rates of alcohol consumption relative to England (Hart et al., 1999), despite relatively low liver disease mortality in the 1950s (Reid, 2008), underscore how behavioural risk factors have intensified over time. Similarly, the rise of heroin use has played a significant role in more recent decades. Scotland’s ongoing drug mortality crisis have been traced to a cohort of users from the 1980s–1990s, and drug-related causes now account for a large share of the excess mid-life deaths (Walsh, et al., 2010). In addition to direct causes such as overdose or suicide, several alcohol- and tobacco-related cancers,

² Eliminating the gap would decrease heart and cancer related mortality by 40% (Scarborough, et al., 2011).

³ The Scottish winter months have been found to have a 30% higher mortality spike than the summer months. Additionally, there is a lagging (1-week) effect between temperature change and mortality. A 1 degree Celsius change in temperature is associated with a 1% increase in deaths (Gemmell, et al., 2000).

such as oesophageal, liver, and lung cancer, also contribute significantly to Scotland’s excess mortality (Whyte & Ajetunmobi, 2012).⁴ These conditions, while medically distinct, share similar behavioural, socioeconomic, and policy-related origins, and are increasingly understood as part of the wider pattern of despair-related deaths. Some researchers trace these trends back to the broader impact of neoliberal economic reforms introduced during the 1980s, which are argued to have compounded health inequalities and widened social vulnerability (Walsh et al., 2016).

Some scholars come to the conclusion that the Scottish Divergence is unlikely to be explained by any single factor (Walsh, et al., 2010; Walsh, et al., 2016; Whyte & Ajetunmobi, 2012; Reid, 2008; Reid, 2011). Rather, the evidence points to a cumulative and multi-causal process. Walsh et al. (2016), applying Bradford Hill’s criteria to over 40 hypotheses, argue that the divergence reflects a “layered vulnerability”, shaped by historic overcrowding, low birth weights, urban policy failures, deindustrialisation, and neoliberal policies during the 1980s, which are argued to have compounded health inequalities and widened social vulnerability (Walsh et al., 2016). Cowley et al. (2016) collected a total of 17 hypothesis behind the “Glasgow Effect” which point to a complex web of “stressors,” encompassing social, environmental, and cultural dimensions.

3 Data

Following the existing literature, life expectancy data used in this study are principally sourced from the Human Mortality Database (HMD), which is a joint data collection effort by the Department of Demographics at the University of California Berkeley (USA), the Max Planck Institute for Demographic Research in Rostock (Germany), and the Institut National d’études Démographiques (INED) in Paris (France). The HMD is overseen

⁴ While mortality from several causes, such as breast cancer, colorectal cancer, pancreatic cancer, and cerebrovascular disease, has declined in Scotland relative to Western Europe, Scotland now performs significantly worse in areas often associated with despair-related and behavioural mortality. These include oesophageal cancer, stomach cancer, chronic liver disease, suicides, external causes, COPD, and motor vehicle accidents. In particular, Scotland ranks poorly for lung cancer, ischaemic heart disease (IHD), chronic liver disease, and suicides (Whyte & Ajetunmobi, 2012).

by Vladimir Shkolnikov (Director from the Max Planck Institute), Magali Barbieri (Associate Director from UC Berkeley and INED), and John Wilmoth (Founding Director from the United Nations and previously UC Berkeley) (HMD, 2021).

3.1 Life Expectancy

The datasets available on the HMD contain originally calculated figures for uniform life expectancy, death rates and other related measures. These values are derived from public data on births, deaths, population estimates and census information. Values are available for all periods where vital statistics and census data are available (Wilmoth, et al., 2021).

Our models are primarily constructed using time series data with the dependent variable being Life Expectancy at Birth (*LEB*) or Life Expectancy at Age x (*LEA_x*). These measures are both functions of mortality rates. They are contained in the HMD's Life Tables and are estimated based on the probabilities of death, which are computed using death rates and “standard methods” (Wilmoth, et al., Brief Summary of the Methods Protocols for the Human Mortality Database, 2017). *LEB* is a measure of all individuals in a population, while *LEA_x* measures only the remaining life expectancy for the population at a given age. In particular, in the HMD, *LEA_x* is calculated as follows:

$$LEA_x = \frac{T(x)}{l(x)}$$

, where $T(x)$ = a person's remaining years from age x ,⁵

$l(x)$ = number of persons alive at age x , also known as the

⁵ $T(x) = \sum_{i=x}^{109} L_i + \frac{1}{2}L_{110}$ for ages $x = 0, 1, \dots, 109$ (Wilson & Foster, 2017).

survivorship function (Wilmoth, et al., 2021).⁶

In this study, we use the HMD's period LEB, rather than so-called cohort LEB, which is consistent with the previous literature (see, e.g., McCartney, et al., 2012, and Anderson and Roughley, 2018). Both cohort and period level LEB are available from the HMD. Cohort LEB represents the life expectancy from a given set of individuals considering their mortality histories (Wilmoth, et al., 2021). Cohort LEB, however, requires the cohorts to pass before it can be computed and, as such, the data is only available up to 1990. The period LEB, by contrast, represents an estimated value based on mortality conditions at a point in time and assumes that mortality rates remained constant through the individuals' lives (Anderson & Roughley, 2018; Wilmoth, et al., 2021). Thus we refer to 'period LEB' simply as LEB for simplicity.

LEB are available for each country on an annual basis and are reported separately by sex (male, female and combined for both). In what follows, we denote these as LEB^s , where $s \in \{\text{male, female, both}\}$. All three series are observed and modeled. Additionally, the HMD provides life expectancy estimates at various ages, denoted as LEA_x^s . The following set of age values are observed and modeled: $x \in \{0, 1, 5, 15, 25, 35, 45, 55, 65, 75, 85\}$.

The analysis is restricted to the period from 1860 to 2017. Although data for Scotland is available from 1855, we begin in 1860 to improve comparability across countries and to minimise distortions arising from irregularities in the earliest years. Not all countries have continuous coverage over the full period. To enhance consistency, we limit the sample to countries in the Western world - defined here as Western Europe, the United States, and Canada⁷. This focus introduces a degree of homogeneity that facilitates the construction of credible

⁶ For ages where $x > 0$, $l(x)$ is derived recursively from the mortality rate at age x , or $m(x)$, as $l(x + 1) = l(x) * e^{-m(x)}$. Here, $l(0)$ is the radix of the life table and is set arbitrarily to 10^5 (Strauss, et al.). This can alternatively be expressed as $l(x) = l(0) \times \prod_{i=0}^{x-1} p_i$ (Wilmoth, et al., 2021).

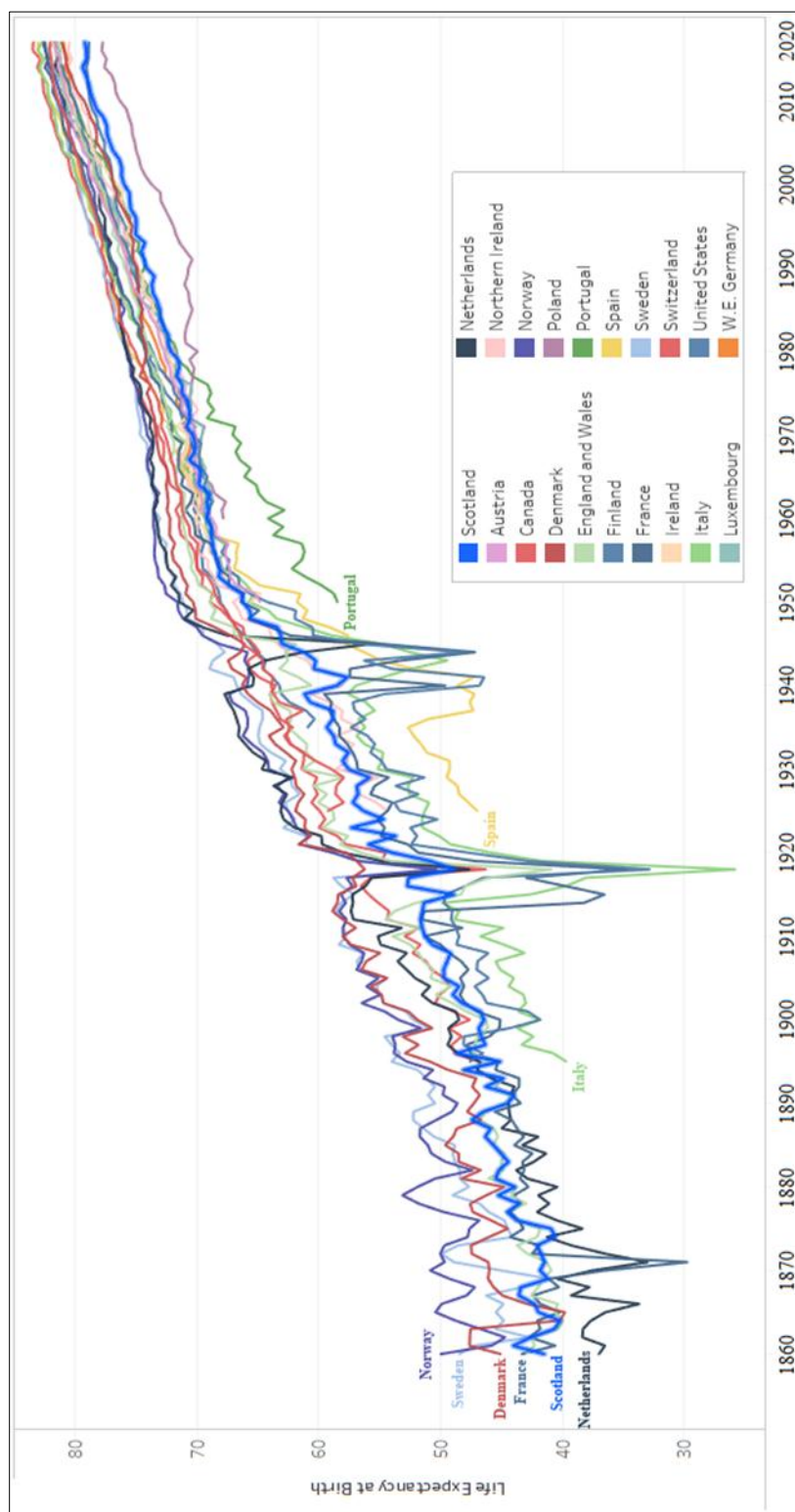
⁷ As shown below, the inclusion of the United States and Canada doesn't impact the models either way, as they receive negligible weight.

counterfactuals, which is especially important for the synthetic control group. Further, in the HMD, Germany is separated into West Germany (1956 to 2017) and East Germany (1956 to 2017) as a unified German series is not available until after reunification in 1990. Because several of the covariates used in the synthetic control modelling are only available for the unified Germany, we construct the time series for the whole of Germany, which we label W.E Germany. by computing a population-weighted average of East and West Germany for each year from 1956 to 2017:

$$W.E. Germany_t = \frac{\sum_r (Pop_{r,t} \cdot e_{r,t})}{\sum_r Pop_{r,t}}$$

Here, $Pop_{r,t}$ is the population of region r in year t , and $e_{r,t}$, represents LEB of region r in year t . The resulting series is close to the official unified German in the year post-1990, when they overlap. The final set of countries used in the analysis are shown in Table 1 below, which outlines the key summary stats based on LEB for each country, with further detail in Table 1.A in the appendix. The overall trend in LEB for all available countries can be seen in Figure 1.2 below.

Figure 1.2: Long-term Life Expectancy at Birth (LEB) Trends by Country, 1860-2017



Note: This figure shows life expectancy at birth for all countries included in the dataset, plotted from 1860 through 2017. Each line represents a single country, allowing for direct comparison of long-run mortality trends across the full observation period.

The summary statistics by country and sex are reported in Tables 1–3, which present life expectancy at birth for the total population (Table 1.1), males (Table 1.2), and females (Table 1.3). Across all three tables, Scotland consistently exhibits the lowest or among the lowest mean life expectancy figures among the included countries. This pattern is particularly evident when compared to the UK neighbours, England and Wales, which show markedly higher averages throughout the period. In Table 1.1, which reports life expectancy for the total population, Scotland records the lowest mean life expectancy at 66.99 years, compared to 68.82 years in England and Wales, and well below many continental countries such as Italy (74.84), Switzerland (74.27), or W.E. Germany (75.27). The range of life expectancy values in Scotland is also large, suggesting long-run volatility.

Table 1.6

Table 1.1: Summary Statistics of Life Expectancy at Birth (Total Population)

Country	Period	Mean	Median	StdDev	Min	Max
Scotland	1860-2017	66.99	70.34	10.31	40.18	79.38
England and Wales	1860-2017	68.82	72.09	10.83	39.93	81.39
Netherlands	1860-2017	72.23	73.05	10.95	31	81.73
Denmark	1860-2017	69.91	73.25	9.05	39.8	81.11
Finland	1860-2017	69.31	71.58	10.36	32.85	81.5
France	1860-2017	67.72	71.51	12.53	29.74	81.42
Sweden	1860-2017	72.48	74.79	9.28	30.45	84.36
Norway	1860-2017	72.01	74.01	9.07	44.71	82.63
Italy	1872-2017	74.84	74.7	3.82	68.63	82.31
Switzerland	1885-2017	74.27	75.02	5.28	60.35	82.48
Canada	1925-2017	74.26	75.07	5.76	57.94	82.06
Northern Ireland	1925-2017	72.06	73.7	6.4	54.4	80.57
Spain	1925-2017	72.42	75.53	9.37	46.98	83.05
United States	1933-2017	74.36	74.6	4.15	60.35	79.05
Austria	1950-2000	74.56	74.46	4.52	64.81	81.64
Ireland	1950-1990	74.36	73.62	4.1	64.75	81.92
Poland	1960-2017	72.13	70.92	2.84	67.63	77.8
Luxembourg	1960-2017	74.84	74.7	3.82	68.63	82.31
Portugal	1960-2017	72.45	72.45	6.33	58.47	81.5
W.E. Germany	1960-2017	75.27	75.32	3.72	69.24	80.94

Note: Summary statistics for life expectancy at birth (LEB) for the total population across all available countries and sexes. The column “Period” indicates the years covered for each country in the dataset.

This divergence is even more pronounced in Table 1.2, which reports life expectancy for males, where Scotland again has the lowest mean (64.64 years), with England and Wales (66.18), and all other Western countries exceeding this figure - often by substantial margins. Notably, countries such as W.E. Germany, Switzerland, and Italy all show male mean life expectancies exceeding 70 years.

Table 1.2: Summary Statistics of Male Life Expectancy at Birth by Country

Country	Period	Mean	Median	StdDev	Min	Max
Scotland	1860-2017	64.64	67.43	9.32	38.01	77.2
England and Wales	1860-2017	66.18	68.89	10.81	33.39	79.54
Netherlands	1860-2017	68.13	71.35	10.61	32.09	79.61
Denmark	1860-2017	67.95	70.8	8.58	38.86	79.06
France	1860-2017	64.35	67.82	12.17	27.23	78.95
Sweden	1860-2017	69.71	71.85	9.42	39.98	80.32
Norway	1860-2017	70.45	73.68	9.17	44.71	80.85
Italy	1872-2017	67.52	69.91	3.61	60.47	77.44
Switzerland	1885-2017	70.21	70.97	5.28	53.45	80.74
Finland	1895-2017	65.64	67.46	9.06	41.25	78.45
Canada	1925-2017	71.58	71.6	5.53	56.73	79.97
Northern Ireland	1925-2017	69.78	69.35	5.97	53.75	78
Spain	1925-2017	69.41	72.39	9.32	42.91	80.91
United States	1933-2017	70.35	70.97	4.63	58.35	76.51
Austria	1950-2017	71.3	70.89	4.73	62.18	79.28
Ireland	1950-2017	72.02	70.91	4	63.55	80.1
Poland	1960-2017	68.2	66.88	2.65	64.55	73.85
Luxembourg	1960-2017	71.72	71.09	4.61	65.44	79.83
Portugal	1960-2017	69.12	70.15	5.95	55.78	76.1
W.E. Germany	1960-2017	72.15	71.89	3.89	66.5	78.56

Note: Summary statistics for life expectancy at birth for the male population across all available countries. The column “Period” indicates the years covered for each country in the dataset.

In Table 1.3, which presents data for females, the difference is less pronounced, but Scotland still lags behind, with a mean of 69.41 years, compared to 71.42 in England and Wales, and over 74 years in many other European countries. These patterns confirm a persistent disadvantage in life expectancy for Scotland relative to a broad set of Western countries, which is consistent across sex and over the long-run historical record.

Table 1.3: Summary Statistics of Female Life Expectancy at Birth by Country

Country	Period	Mean	Median	StdDev	Min	Max
Scotland	1860-2017	69.41	73.48	9.31	41.5	81.34
England and Wales	1860-2017	71.42	75.19	10.83	41.23	83.2
Netherlands	1860-2017	76.31	76.52	11.42	39.86	83.3
Denmark	1860-2017	71.89	75.7	9.56	40.78	83.12
France	1860-2017	71.18	75.22	12.78	32.58	85.07
Sweden	1860-2017	73.44	76.62	9.42	30.45	82.75
Norway	1860-2017	74.61	77.34	9.27	44.71	84.84
Italy	1872-2017	77.72	78.45	3.82	68.31	84.71
Switzerland	1885-2017	77.03	78.47	5.28	63.45	83.42
Finland	1895-2017	72.86	76.34	10.1	41.85	82.5
Canada	1925-2017	77.07	78.72	5.92	59.14	84.13
Northern Ireland	1925-2017	72.06	74.62	6.52	54.4	80.57
Spain	1925-2017	75.38	78.55	9.3	48.49	85.1
United States	1933-2017	76.64	78.09	4.09	62.09	81.61
Austria	1950-2017	77.57	77.65	4.34	67.28	83.94
Ireland	1950-2017	76.82	76.63	4.15	66.11	83.73
Poland	1960-2017	76.06	75.15	2.84	70.53	81.72
Luxembourg	1960-2017	77.95	78.23	3.96	71.83	83.32
Portugal	1960-2017	75.7	77.07	6.29	61.1	81.02
W.E. Germany	1960-2017	78.09	78.37	3.65	71.75	83.33

Note: Summary statistics for life expectancy at birth for the female population across all available countries.

The column “Period” indicates the years covered for each country in the dataset.

3.2 Covariates

Covariates are used in SCMs to select and weight countries in the synthetic control group to best match Scotland before each breakpoint. These are chosen for their ability to capture factors linked to life expectancy trends across countries. To ensure coverage from 1860 onward, we focus on broad indicators reflecting prosperity, governance, geography, demographics, climate, and population density. We include GDP per capita for each country using the Maddison Project’s data on GDP by country. The Maddison Project is an effort by the University of Groningen’s Groningen Growth and Development Centre (GGDC) to estimate long-term GDP (Groningen Growth and Development Centre, 2020). Since these are only available for the United Kingdom as a whole, we adjust them using official regional data from 1980 onwards with regional estimates from Geary and Stark for earlier years

(Geary & Stark, 2020; Geary & Stark, 2015; Crafts, 2004). Missing values are linearly interpolated. Given Scotland’s historically stable share of UK GDP, we are confident these estimates provide a reasonable approximation. To account for geographic proximity to Scotland, the longitudinal and latitudinal distances between Glasgow and each country’s largest city is included. The centroid of the city is taken to approximate the city center. Additionally, the population density and the share of the male population are included, both from the HMD data. Finally, an indicator for whether the country is part of the UK is included.

4 Descriptive Trend Analysis

Our analysis begins with a descriptive trend study of Scotland’s long-run life expectancy before introducing the concept of a “synthetic Scotland”. This initial analysis helps identify plausible breakpoints in the historical data, which can then guide the construction of distinct synthetic counterfactuals. Specifically, we compare Scotland LEB and LEA_x to that of the other Western countries - both individually and as a population-weighted average - through simple visual inspection of plotted trends. The population-weighted average for LEB and LEA_x can be denoted by $WAVG$ and expressed as follows:

$$WAVG = \frac{\sum_{i=1}^n (P_{i,t,s,x} e_{i,t,s,x})}{\sum_{i=1}^n (P_{i,t,s,x})},$$

where $P_{i,t,s,x}$ and $e_{i,t,s,x}$ are, respectively, the population and the life expectancy for country i in year t for sex s at age x .

Because the countries in the dataset begin reporting life expectancy in different years, a simple average across all countries by year would produce misleading results. (For example, if early-year data were missing many high-life-expectancy countries, the average would skew low; conversely, the United States, which has a large population with relatively low life expectancy, would unduly pull down a naive average in later years.) Moreover, data reliability varies and civil registration of deaths was not uniformly established across countries in the 19th century. Notably, Scotland introduced compulsory registration in 1855, whereas registration wasn’t fully enforced

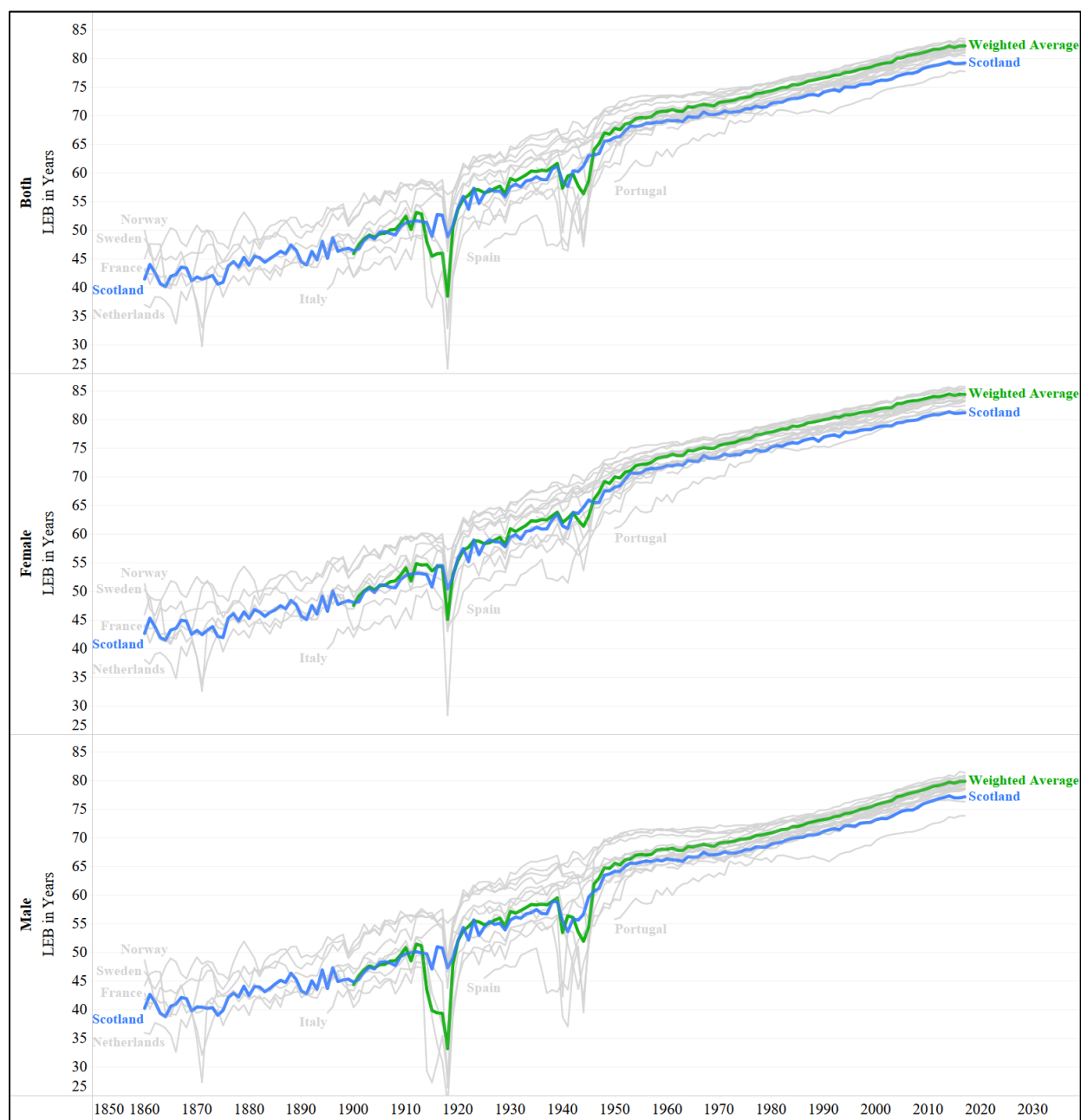
until the 1870s in England & Wales (Cameron, 2007 ; Davis, 2023). Accurate life tables require broad coverage of deaths by age, so early-life-expectancy figures should be viewed with caution if registration was incomplete. In our analysis, we mitigate these issues by using a population-weighted average across countries only for years where data is available for a broad set of countries, ensuring no single nation dominates the trend.

To mitigate this issue, we construct a fixed comparison group composed of countries with uninterrupted data coverage from at least 1900 onwards. While this restriction narrows the geographic scope to Western Europe, it ensures consistency and avoids overweighting of large countries, that appears late in the dataset and are geographically distant from Scotland, such as the U.S. or Canada. Thus, the remaining countries included in the weighted average are as follows: Denmark, England and Wales, Finland, France, Italy, the Netherlands, Norway, Sweden, and Switzerland. Based on 2017 population figures, these countries represent about 30% of the population in our full dataset but over half of the Western European population. As such, they offer a meaningful and balanced comparison for Scotland.

4.1 Trends in Life Expectancy at Birth

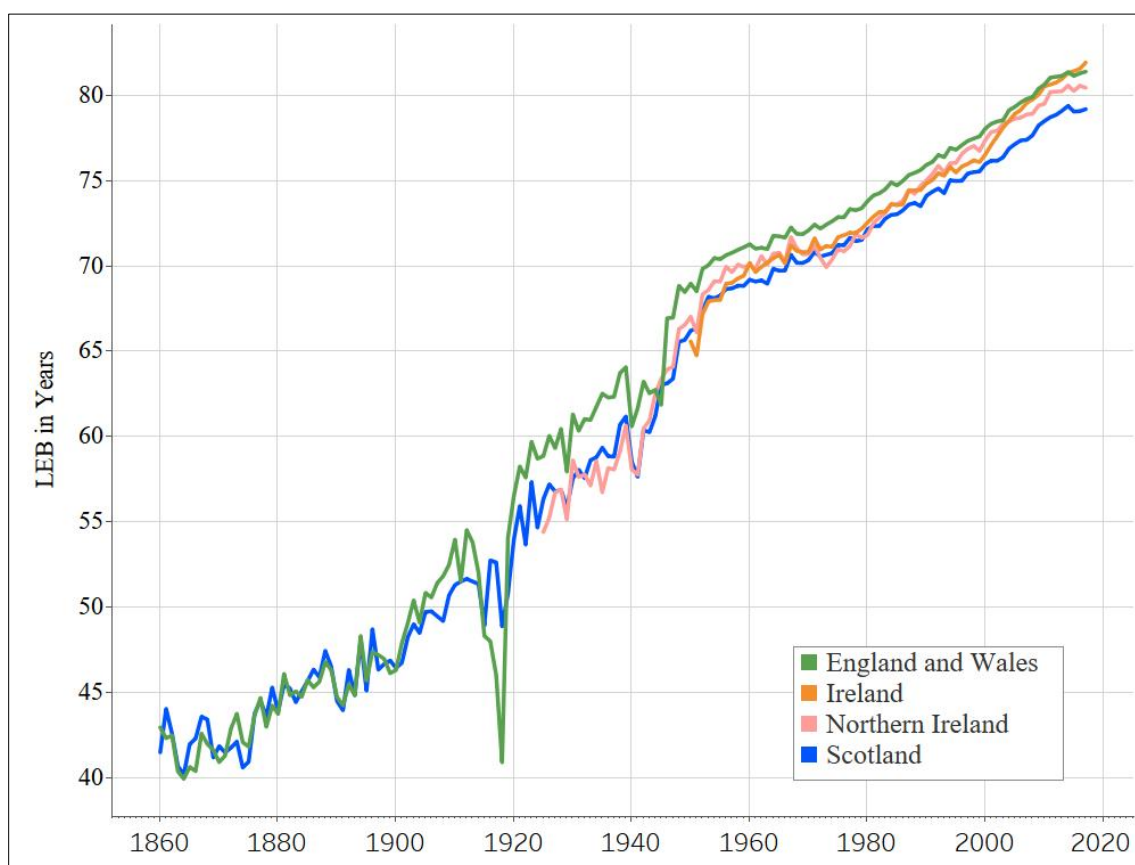
Building upon Figure 1.1, Figure 1.3 plots Scotland's LEB alongside that of each country listed in Tables 1–3, as well as the fixed-basket weighted average described above. The top panel shows trends for the total population, while the lower panels present female and male trends separately. Scotland's LEB closely track the weighted average up to the 1930s. While most countries experienced strong and sustained gains in life expectancy from the 1920s onwards, Scotland's progress appears more subdued.

Figure 1.3: Long-run Life Expectancy at Birth in Scotland vs a Fixed-Basket Weighted Average



Note: Each panel shows life expectancy at birth for all countries in the dataset, with Scotland and the fixed basket weighted average highlighted and other countries muted in the background. The weighted average begins in 1900 and includes Denmark, England & Wales, Finland, France, Italy, the Netherlands, Norway, Sweden, and Switzerland, ensuring consistent coverage over time.

Figure 1.4: Life Expectancy at Birth by British Isle Nations, 1860 - 2017



Note: Each panel shows life expectancy at birth for countries in the British Isles, with all lines displayed in full color rather than muted. The figure includes Scotland, England & Wales (combined), Northern Ireland, and Ireland, allowing for direct within-region comparison over time.

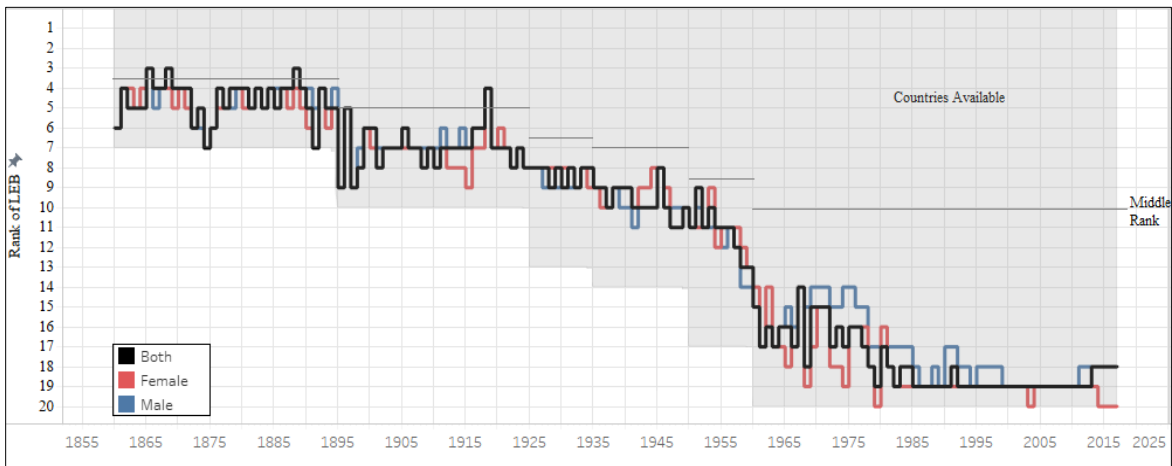
This marks the beginning of a growing gap between Scotland and Western Europe – an early phase of divergence that precedes the post-1950 period often emphasised in existing literature. This is confirmed by Figure 1.5 which zooms in on the UK countries and compares their respective trends in life expectancy. By narrowing the focus to Scotland’s nearest neighbours, a richer picture emerges. For instance, the relative slow growth in Scotland’s LEB is already evident after the year 1900 when compared to England and Wales.

Figure 1.3, Figure 1.3, and Figure 1.4 also reflect the demographic shocks associated with the two World Wars. During World War I, numerous countries in the sample experienced a marked decline in life expectancy at birth (LEB). Although the most significant decreases were observed among males, fatalities were not limited to male combatants; some estimates indicate that civilian deaths exceeded those of combatants (Ó Gráda, 2024). A

comparable but less pronounced trend is apparent during World War II, again impacting everyone but disproportionately the male population. These wartime reductions are evident in the weighted average and several country-specific data lines. Scotland appears somewhat less affected than heavily engaged continental countries, particularly during WWI, likely due to differential exposure to direct combat losses.

From the interwar years onwards, Scotland began to lag behind the Western European average. This divergence deepens markedly after the 1950s. During this period, much of Western Europe experienced a rapid acceleration in life expectancy, supported by expanding welfare states, improvements in housing, public health, and medical care. While Scotland’s LEB rose, it was slower than the broader Western Europe, particularly for females. By the 1970s and 1980s, Scotland consistently ranked near the bottom of the distribution, a position it has continued to hold in the decades since. By 2017, Scotland remained well below both the weighted Western European average and most individual countries in the sample.

Figure 1.5: Ranking Scotland’s LEB Over Time Against Varying Baskets of Countries



Note: The figure shows the annual ranking of Scotland’s life expectancy at birth relative to a set of similar countries over time. Rankings are plotted separately for the total population (black), females (red), and males (blue). The number of countries included in the comparison changes over time and is indicated by the grey shaded area. A higher rank indicates better relative performance. The horizontal think lines mark the median position (middle rank) among the available countries in each period.

Figure 1.5 tracks Scotland’s rank in LEB relative to the comparator countries over time for females, males and for both. From the outset, Scotland occupies a position consistently below the median rank, indicated by the

horizontal black line. While it is closer to the middle in the late 19th and early 20th century, it is important to note that it never rose above it except in two years. As more countries enter the dataset over time, the total number of comparators changes, limiting strict comparability across years. Nevertheless, the trend is clear; Scotland's relative position is never near the top and deteriorates notably between the mid-1950s and 1980, falling into the bottom quartile and remaining there. This downward shift is visible for both males and females, though it occurred more rapidly for women. By the 1970s, Scottish females were consistently ranked second to last, while Scottish males reached similar positions only by 2000.

Notably, the sex-specific trends (Figure 1.3, bottom panels) imply that Scotland's post-1970 divergence was driven more by women's slower life expectancy gains than men's. In the 1960s, the average deficit from the weighted average for females and males were 1.75 years and 1.74 years respectively. By the 1980s, the gap had widened to ~2.9 years for women (as compared to ~2.1 for men), and similar differences persisted into the 1990s.⁸ Note that the "weighted average" benchmark is recalculated each year using that year's population weights for the comparison countries; the weights are not fixed over time, but reflect each country's population share in each particular year. Looking at the very recent trends, life expectancy gains have slowed globally, a trend first seen in the U.S. around 2009 - 2010 and later observed across many Western countries by 2015. In both the U.S. and Europe, this slowdown has been linked to rising "deaths of despair", especially among younger working-age adults Europe (Allik, et al., 2020; Case & Deaton, 2020). Within Europe, Scotland is among the most affected, experiencing a marked drop in life expectancy in 2015 and only limited recovery since. While Case and Deaton (2020) emphasise the role of deaths among working-age white males without a college degree in the U.S., the stagnation in Scotland appears to affect both women and men equally as evidenced by the lines in Figure 1.3.

⁸ Weights for the "world average" life expectancy were computed using each country's share of the total population in that year (for the set of countries with data in that year). We verified that using a fixed weighting (e.g. average population share over 1900–2000) yields a very similar trajectory for the average deficit, so the pattern described is robust.

Finally, while this has been noted earlier in passing, this pattern warrants more direct emphasis. A closer inspection of Figure 1.3 and Figure 1.4 reveals a subtle yet consistent feature that appears largely overlooked in the existing literature: across all major recovery periods, life expectancy rises in every country, including Scotland, yet Scotland's rate of improvement is persistently weaker. This is particularly evident in the post-war periods, when other Western countries experience sharp rebounds, while Scotland's gains remain comparatively slower. Crucially, this weaker performance is not confined to the 1950s. Although Scotland appears near the median at the beginning of the sample and broadly tracks the weighted average into the early twentieth century, a more careful reading indicates that its rate of improvement began to lag marginally by the turn of the century, and that lag grew following WWI. This earlier divergence is particularly evident when compared with England and Wales. This early underperformance is especially clear when contrasted with England and Wales. Across four major recovery episodes—around 1900, 1919, 1946, and 1955—life expectancy increases in Scotland, but the gradient is consistently flatter than in comparator countries. Taken together, this recurring pattern suggests that Scotland's relative decline is not driven by discrete shocks alone but reflects a more persistent tendency toward weaker recovery dynamics.

4.2 Trends in Life Expectancy at Different Ages

LEA_x measures only the remaining years of life, which will be fewer and less elastic to changes for the oldest age groups. LEA_x can be difficult to analyse given differences in scale. We thus normalise the data, first by adding the LEA e_x to the current age x . We then calculate the percentage difference d between the log of the weighted average and the log of Scotland's values in the following way:

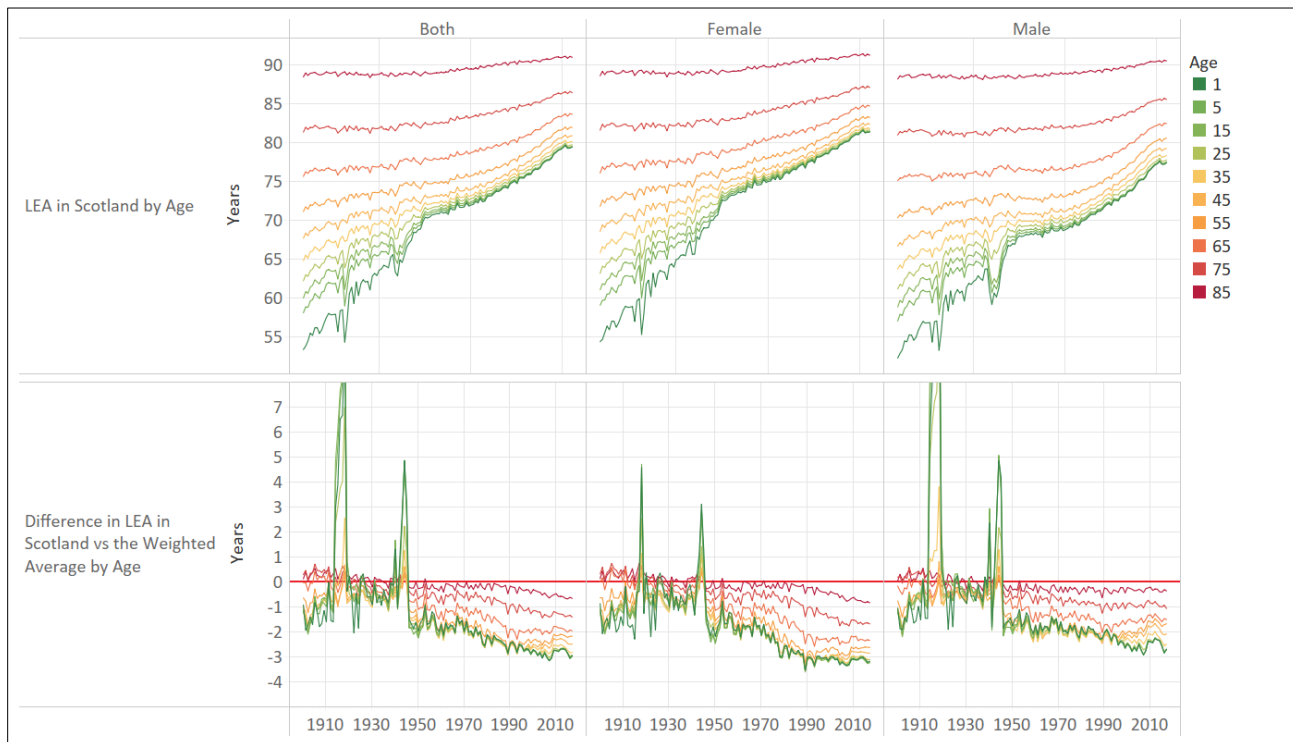
$$a = e_x + x$$

$$d = \frac{\log a_W - \log a_S}{\log a_S}$$

where W is the weighted average, S is Scotland. The results are very similar but scaled more accurately.

Figure 1.6 shows that mortality rates in Scotland have exceeded the weighted average for all age groups since shortly after WWI. Mortality rates are specifically high in Scotland for working age individuals, as suggested by Anderson (2018) and Allik (2020). However, examining LEA gaps between Scotland and our weighted average, we find that the greatest deficits are shared by infants, children and young working age individuals. These results have been consistent for most of the last century barring wartime. This trend also holds across sexes.

Figure 1.6: Life Expectancy at Age x (LEA_x) and Deficit Relative to the Weighted Average by Sex



Note: The top row shows life expectancy at different ages (x) for Scotland over time, with separate panels for the total population, males, and females. Each line represents a specific age band, depicting how remaining life expectancy from that age has evolved historically.

The bottom row shows the same measure expressed as the difference between Scotland and the fixed-basket weighted average, so that values below zero indicate an LEA_x deficit relative to the comparison countries.

This layout highlights which age groups experienced the largest shortfalls in life expectancy over time.

5 Methods for Synthetic Control

The long-run descriptive and trend analysis in the previous section provides important motivation for a more formal and robust comparative assessment of Scotland's life expectancy trajectory. First, it underscores the need for a credible counterfactual benchmark against which Scotland's performance can be meaningfully assessed. While the population-weighted average of other Western European countries offers a useful baseline, recent advances in programme evaluation - particularly the Synthetic Control Method (SCM) - provide a more data-driven and flexible approach for constructing tailored comparison groups. Unlike simple averaging, the SCM constructs a synthetic Scotland as a weighted combination of comparator countries, where weights are selected endogenously to closely replicate Scotland's pre-divergence characteristics and life expectancy trajectory.⁹ Second, the descriptive analysis reveals a strikingly consistent pattern: following each major recovery period, Scotland's life expectancy does increase, but at a systematically slower rate than its peers. This persistent pattern, evident even relative to England and Wales, suggests a tendency toward slower gains rather than discrete collapses.

While the SCM is typically applied in settings where a clearly defined intervention or shock delineates the point at which outcomes may diverge from a counterfactual trajectory, there is no singular, known intervention to evaluate here. Instead, the objective is to assess when Scotland's life expectancy begins to depart persistently from plausible counterfactual paths. To this end, the inflection points identified in the descriptive trend analysis are treated as reference breakpoints that anchor separate SCM models. For each breakpoint, a synthetic Scotland is constructed using only pre-break information, and the post-break evolution of observed outcomes is compared to this counterfactual trajectory to quantify the timing and magnitude of divergence.

⁹ No actual "treatment" occurred here as it would in a clinical trial or observable policy deployment; rather, we use the term to mean the point when Scotland's mortality trend potentially diverged due to an unobserved factor or factors (the hypothetical intervention).

For this study, we focus on six such breakpoints since 1900 (1900, 1919, 1946, 1955, 1970, and 1980). The first four were selected based on the descriptive analysis, where it was observed that they correspond to sustained shifts in the long-run trend or in the population health literature. The 1970 and 1980 breakpoints were also included as Scotland's relative public health disadvantage has worsened continuously since this period. Some have hypothesized that this is due to deindustrialization and a loss of manufacturing, which resulted in increased unemployment and thus increases in mortality among working-age populations driven by alcohol, drugs, violence, and suicide (McCartney et al., 2012; Parkinson, et al., 2017; Walsh, et al., 2010). Still, the attribution dates of these studies vary between the 1970s and 1980s.^{10,11}

During the implementation of the Synthetic Control Method (SCM), weights are assigned to each country in the donor pool such that the weighted combination of control units closely matches Scotland's pre-breakpoint characteristics and life expectancy trajectory. These weights are chosen to minimize the mean squared prediction error (MSPE) over the pre-break period, ensuring that the synthetic control provides the closest possible approximation to Scotland prior to divergence. Formally, this involves selecting a vector of weights $W = (w_2, \dots, w_{c+1})'$ that minimises the distance between a vector of pre-breakpoint covariates of Scotland, denoted by

¹⁰ In practice, SCM models were estimated at regular five-year intervals from 1900 through 2015, supplemented by additional specifications aligned with major historical events, including the post-World War I/Influenza epidemic period (1919) and the aftermath of World War II (1946). This systematic approach reflects the absence of a singular intervention date and provides a transparent means of assessing whether divergence patterns are sensitive to breakpoint selection. While a large number of models were evaluated, the analysis presented here focuses on six breakpoints that most clearly correspond to the onset of sustained and economically meaningful divergence. Adjacent specifications around key breakpoints (e.g., 1919 versus 1920) yield substantively similar results, indicating that the findings are not sensitive to minor variations in breakpoint definition.

¹¹ Given the substantial volatility in mortality conditions during wartime - particularly the coincidence of World War I with the 1918-1919 influenza pandemic - additional specifications were estimated excluding wartime years to focus on underlying recovery dynamics and reduce the influence of short-run fluctuations in life expectancy. In these models, wartime (1914-1919 and 1939-1945) observations are removed for all countries; the remaining time series is re-indexed to preserve sequential structure for estimation. After estimation, results are remapped back to calendar years for interpretation. These models produce patterns of divergence consistent with the main results, reinforcing the interpretation that observed gaps reflect persistent differences in recovery rather than artifacts of crisis-period volatility. Results data tables and code are available upon request.

X_l , and the corresponding weighted average of the same covariates in the donor pool, X_0W . The minimization problem is defined as:

$$\min_W \sum_{m=1}^k v_m (X_{1m} - X_{0m}W)^2$$

, where v_m denotes the “relative importance” of the m -th variable in the matching process. X_1 is a $(k \times 1)$ vector containing Scotland’s LEB values prior to the breakpoint date. X_0 is the matrix $(k \times c)$ of the corresponding values for the c control countries in the donor pool. Two constraints have to hold. First, weights must be non-negative, i.e., $0 \leq w_j \leq 1$. Second, the sum of weights must equal one, i.e., $w_2, \dots, w_{j+1}=1$.

To evaluate the quality of the SCM fit, one must assess how closely the synthetic Scotland’s LEB replicates the trajectory of observed Scotland’s LEB in the pre-breakpoint period. This can be evaluated visually by inspecting how well the synthetic and observed path align prior to the break. Again, this can be evaluated more formally using the MSPE, which quantifies the average squared difference between Scotland’s observed LEB and that of the synthetic control in the pre-break period, offering a direct measure of model accuracy.

Note that the composition of the donor pool varies across models, reflecting differences in data availability over time. For example, in the 1900 model, only seven countries have complete data prior to the break date of 1900. These seven countries have data available for both males and female independently, and thus only these are used to construct the synthetic control. Models for later periods, such as 1955 or 1980, draw on a larger pool of countries as more national series become available. Table 4 summarises the donor pool composition for each model.

For each model, we compare Scotland’s actual LEB trajectory to that of its synthetic counterpart to assess whether divergence occurred, when it began, and how large it became. In the 1919 model, for example, the synthetic Scotland is constructed using only pre-1919 data. Any post-war gap between the observed and synthetic

trends is interpreted as evidence of divergence emerging after the First World War. This approach enables us to trace not only the possible onset and persistence of divergence over time, but also to quantify its magnitude year by year, and by 2017.

In addition to estimating separate SCMs for each breakpoint, we conduct the analysis across multiple demographic classifications. Specifically, for LEB, we estimate models for the total population, as well as separately for females and males. This yields 18 LEB models in total: 6 breakpoints $\times$ 3 demographic groups. For LEA_x , we extend this approach at 10 specific ages (1, 5, 15, 25, 35, 45, 55, 65, 75, 85). For each age, we estimate separate SCMs by gender (male, female, total) and by breakpoint. This results in 198 LEA models:

$$6 \text{ breakpoints} \times 3 \text{ gender groups} \times 11 \text{ age groups}$$

Together with LEB models, these produce a total of 216 SCM estimates, enabling a comprehensive assessment of divergence patterns across time, age, and gender.

Table 1.4: Donor Countries by Synthetic Control Model and Period

Model	1900 Model	1919 Model	1946 Model	1955 Model	1970 Model	1980 Model
Period	(1860-2017)	(1895-2017)	(1925-2017)	(1935-2017)	(1950-2017)	(1950-2017)
Donor Pool	Scotland	Scotland	Scotland	Scotland	Scotland	Scotland
	England/Wales	England/Wales	England/Wales	England/Wales	England/Wales	England/Wales
	France	France	France	France	France	France
	Denmark	Denmark	Denmark	Denmark	Denmark	Denmark
	Netherlands	Netherlands	Netherlands	Netherlands	Netherlands	Netherlands
	Norway	Norway	Norway	Norway	Norway	Norway
	Sweden	Sweden	Sweden	Sweden	Sweden	Sweden
		Finland	Finland	Finland	Finland	Finland
		Italy	Italy	Italy	Italy	Italy
		Spain	Spain	Spain	Spain	Spain
		Switzerland	Switzerland	Switzerland	Switzerland	Switzerland
			Canada	Canada	Canada	Canada
			N. Ireland	N. Ireland	N. Ireland	N. Ireland
				Austria	Austria	Austria
				Ireland	Ireland	Ireland
				Portugal	Portugal	Portugal
				United States	United States	United States
					Luxembourg	Luxembourg
					Poland	Poland
					W.E. Germany	W.E. Germany

Note: Each column lists the countries included in the donor pool for a specific Synthetic Control Model, named by its breakpoint year (e.g., the “1900 Model”). The year in parentheses indicates the period used to estimate the model. For example, “1900 Model (1860–2017)” refers to a model calibrated on data from 1860 to 2017.

6 Results

The Synthetic Control Models enables us to evaluate Scotland’s history through a new lens. Instead of examining Scotland respective to all western or Western European countries, a basket of weighted countries that are most like Scotland historically is derived. Additionally, the counterfactual allows us to observe what could have occurred from a specific point in time, *ceteris paribus*.

6.1 Country Weights

Country weights are derived using the SCM as per equation 4, which assigns higher weight to countries whose pre-break life expectancy trends closely match Scotland's. All country weights by model, sex and age are reported in Table 1.7 in the Appendix. While the details vary by model, demographic group and age, a clear pattern emerges. England and Wales dominate the early models, with Northern Ireland becoming more prominent from 1925 onwards, and the Republic of Ireland contributing in the more recent models. Together, these neighbours account for most of the weighting. In the 1919-breakpoint synthetic control model, Switzerland carries a notably high weight. This is likely because of differences in World War I impact; England & Wales saw extreme swings in life expectancy (a 31.5% collapse from 1913–1918), whereas Switzerland (like Scotland, as well as Ireland) remained relatively stable through the conflict. The SCM algorithm, seeking to match Scotland's pre-1919 trend, therefore leans heavily on stable-weight countries like Switzerland while assigning little weight to more volatile countries like England & Wales.¹² In later models (1946 and 1955), Northern Ireland carries about 60-70% of the total weight while England and Wales contribute around 20%. The rest contribute very little or nothing at all. In the more recent models (1970 and 1980), all countries from the British Isles – including Ireland, which enters the dataset in 1950¹³ – contribute to the counterfactual. England and Wales, however, remain the least weighted among them. These models also show more heterogeneity, with countries such as Luxembourg, Austria, Finland, and occasionally others receiving dominant weights in certain age- or sex-specific models. As more countries are included, the composition of weights becomes more varied across specifications.¹⁴

¹² For each SCM, the chosen country weights are constant over time in the post-break analysis, but they are determined by that country's stability and similarity to Scotland in the pre-break period.

¹³ While BDM data was collected in Ireland prior to the 1950s, the HMD doesn't contain pre-1950 estimates for the Life Expectancy at Birth due to data quality concerns and "limited availability of data on population counts and deaths" prior (Jasilionis, 2025).

¹⁴ We observe cases where the both-sexes model has different country weights (or covariate weights) than either the weights assigned for males or females would indicate. This is because the aggregate demographic groups are modelled and optimized independently of the demographic specific models.

6.2 Covariate Weights

Covariates are presented as a weighted value totaling 1 across all six, but the influence of these variables differs between models. Generally, it is the pre-break LEB and LEA timeseries data that most inform the model. Models with different sets of covariates were run, and the country weightings changed only slightly.¹⁵

The covariate weightings that we observed are largely model specific, and they vary by demographic group or breakpoint observed. However, there are some consistencies worth noting. First, latitudinal distance was hypothesised to have a greater impact than longitudinal distance – potentially serving as a measure for weather (or temperature). This was not the case. Latitude only contributed marginally, but longitude was a driving factor in many models. Second, the earlier the model, the more heavily weighted GDP/per capita was (though it was important for the Modern.1980 model with men). All other covariates shared importance in matching the counterfactual to Scotland in the pre-breakpoint years. [See all country weightings in Table 1.8.]

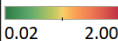
6.3 Mean Squared Prediction Error

Across most models, we observed reasonably small Mean Squared Prediction Errors (MSPE). Again driven by tumultuous data around the world wars, the only outliers in MSPEs that we saw were most concentrated to males, younger age brackets and in models with breakpoints around periods of global conflict. These results are summarised in Table 1.5.

¹⁵ As Scotland's nearest neighbors were consistently the highest weighted countries, models excluding distance between largest cities, including them as a single distance between points and measuring based on capital city were all run for robustness. Similar covariate weights were applied in many cases, and the resulting counterfactuals and country weights were not significantly different.

Table 1.5: Model Mean Squared Prediction Errors Values

		All Ages	0	1	5	15	25	35	45	55	65	75	85
Century.1900	Both	0.69	0.69	1.35	0.96	0.54	0.49	0.37	0.58	0.68	0.11	0.47	0.06
	Female	1.01	0.61	1.60	1.09	0.49	0.40	0.47	0.52	0.42	0.08	0.19	0.04
	Male	0.59	0.58	1.52	1.04	0.54	0.39	0.15	0.44	0.12	0.04	0.03	0.04
Post.WWI.1919	Both	2.22	2.10	3.14	1.23	1.34	1.97	0.48	0.09	0.10	0.47	0.31	0.34
	Female	1.74	1.73	2.67	1.16	0.70	0.40	0.27	0.52	0.11	0.27	0.28	0.06
	Male	2.47	2.36	7.59	5.28	1.45	0.90	0.40	0.23	0.19	0.04	0.22	0.27
Post.WWII.1946	Both	0.54	0.29	0.29	0.28	0.14	2.02	0.87	0.18	0.05	0.02	0.04	0.21
	Female	0.29	0.26	0.21	0.11	0.17	0.13	0.10	0.09	0.09	0.08	0.11	0.14
	Male	1.90	1.12	1.35	1.12	0.97	0.62	0.36	0.19	0.07	0.05	0.05	0.03
Post.WWII.1955	Both	0.37	1.07	0.42	0.39	0.46	1.32	0.54	0.21	0.09	0.03	0.03	0.09
	Female	0.30	0.41	0.41	0.37	0.31	0.24	0.19	0.15	0.13	0.09	0.05	0.06
	Male	2.08	1.23	1.78	1.66	1.58	0.96	0.45	0.29	0.16	0.07	0.07	0.06
Modern.1970	Both	0.13	0.30	0.39	0.43	0.54	0.50	0.44	0.29	0.10	0.03	0.03	0.03
	Female	0.10	0.09	0.10	0.10	0.09	0.09	0.08	0.07	0.08	0.06	0.04	0.02
	Male	1.08	0.66	1.15	1.14	1.08	1.05	1.02	0.87	0.43	0.16	0.05	0.02
Modern.1980	Both	0.08	0.15	0.08	0.30	0.19	0.29	0.29	0.14	0.10	0.03	0.08	0.04
	Female	0.05	0.04	0.05	0.04	0.05	0.05	0.06	0.05	0.05	0.06	0.04	0.04
	Male	0.13	0.13	0.16	0.17	0.18	0.28	0.39	0.38	0.32	0.18	0.06	0.04


0.02 2.00

Note: This table reports the mean squared prediction error (MSPE) for each synthetic control model across all breakpoints and sexes. The first two columns list the model and sex, and subsequent columns show MSPE values for all ages combined and for each selected age (1, 5, 15, ..., 85). Lower values indicate a closer fit between the synthetic control and actual pre-break trends, while higher values (highlighted in red) signal weaker pre-break fit.

The 1919 models have the least accurate pre-breakpoint fit, but most are good approximations of Scottish data.

Overall, counterfactuals align more closely with pre-breakpoint results than any individual country or weighted average.

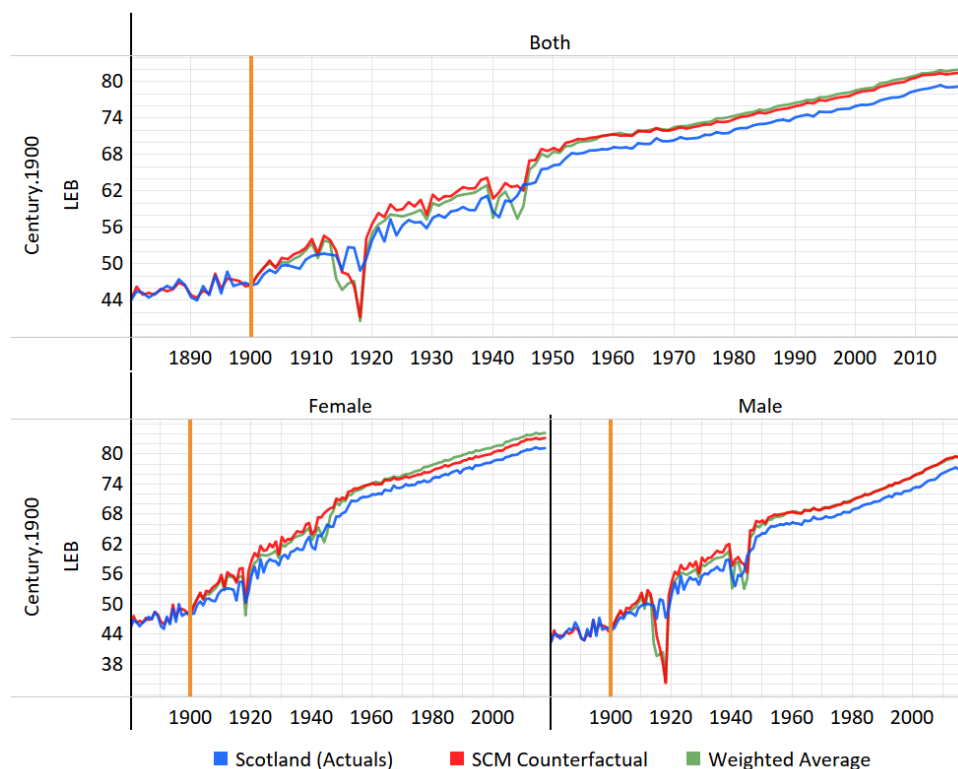
6.4 Counterfactual Results

The counterfactuals suggest that the Scottish Divergence occurred during two time periods. Scotland was similar to the weighted average until the interwar period. Observationally, we see this in England and Wales' acceleration above Scotland in the five years leading into WWI, but many countries first experienced rapid expansion following the war. Comparative model results suggest that by the end of the interwar period, growth in Scotland was already outpaced by others and at least half of the contemporary three-year life expectancy deficit was foreseeable. Visual analysis confirms this, pointing to a lag being established by 1931. Still, aligning with many

of the studies that point to policies and events between the 1960s and 1980s, we observe a second divergence which likely occurred by 1970. Other countries again began to outpace Scotland. Counterfactuals suggest that had adjustments been made by 1970 or 1980 that resulting in a similar growth rate to others, Scots' lifespan could have been 1.5 years longer on average from that point. These results are summarised in more detail and by breakpoint here.

The 1900 results illustrate that Scotland was trending towards a much longer lifespan around the turn of the century. While below the average of 82.2 years (which is about 3.0 years longer than actual Scottish lifespans were in 2017) the model implies that life expectancy could have been 2.2 additional years on average. By sex, the counterfactual projects a lifespan of about 79.6 years (+2.5 years) for males and 83.2 (+2.3 years) for females by 2017. The actual deficits in 2017 were 2.8 and 3.3 years for males and females respectively. This is reflected of the greater relative gap that females have seen through the latter half of the 20th century. By age, potential gains are greatest in the younger working age bracket, followed by children and infants. The model trends are shown in Figure 1.7, and the 2017 results are summarised in Figure 1.13 and Figure 1.14 below.

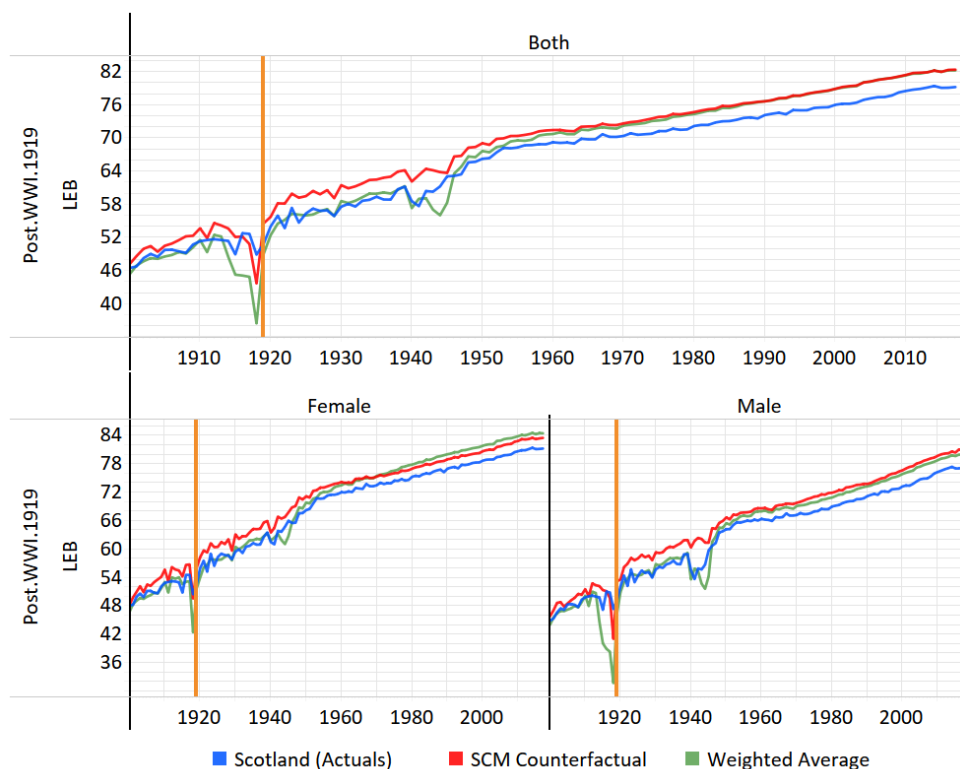
Figure 1.7: Counterfactual, Weighted Average, and Actual Scotland Trends for the Century (1900 Breakpoint)
SCM, 1880 – 2017



Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Century model (1900 breakpoint). “Breakpoint” is a term to mean a potential breakpoint year. The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1880 to 2017.

Given the relatively small impacts of the First World War on Scottish LEB, the country was positioned to be slightly above average in 2017 by 1919. Model results implies that life expectancy could have been 80.9 years for the full population, roughly one year above the average. This was the most positive trajectory across all aggregate models for Scotland, suggesting that the Scottish Divergence had not commenced. Still, it is important to reiterate that England and Wales had experienced significant increases in life expectancy in the few years prior to WWI. The counterfactual results we observe again suggest that males had more of the gain potential in 1919, due to the early models not anticipating changes in female growth rates in the 1960s -1980s. Age-specific life expectancy is consistent with the 1900 breakpoint findings. [See Figure 1.8 below.]

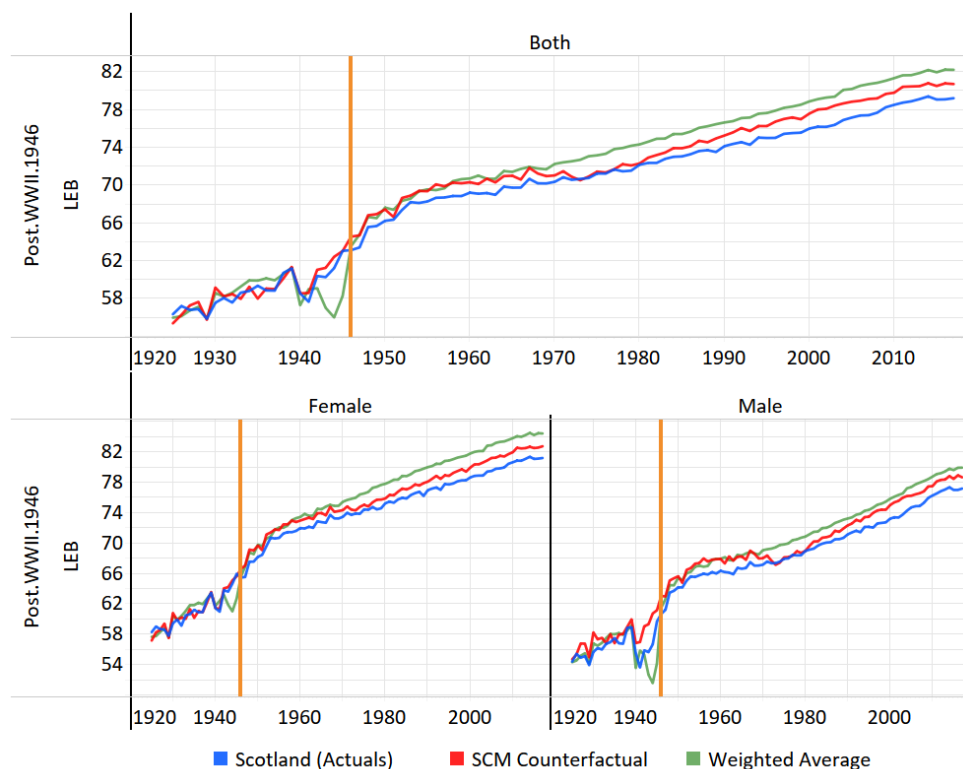
Figure 1.8: Counterfactual, Weighted Average, and Actual Scotland Trends for the Post-WWI (1919 Breakpoint)
SCM, 1900 – 2017



Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Post-WWI model (1919 breakpoint). The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1900 to 2017.

By the time the Second World War began, others had recovered from any lingering effects from WWI. By this point, the counterfactuals suggest an opportunity for only an additional 1.5 years beyond their 2017 value. This additional 1.5 years is explainable by Scotland's already slower growth rate. Had Scotland achieved the rate of change that other's experienced earlier, lifespans would be longer today and the counterfactuals values would be even lower. [See Figure 1.9 below.]

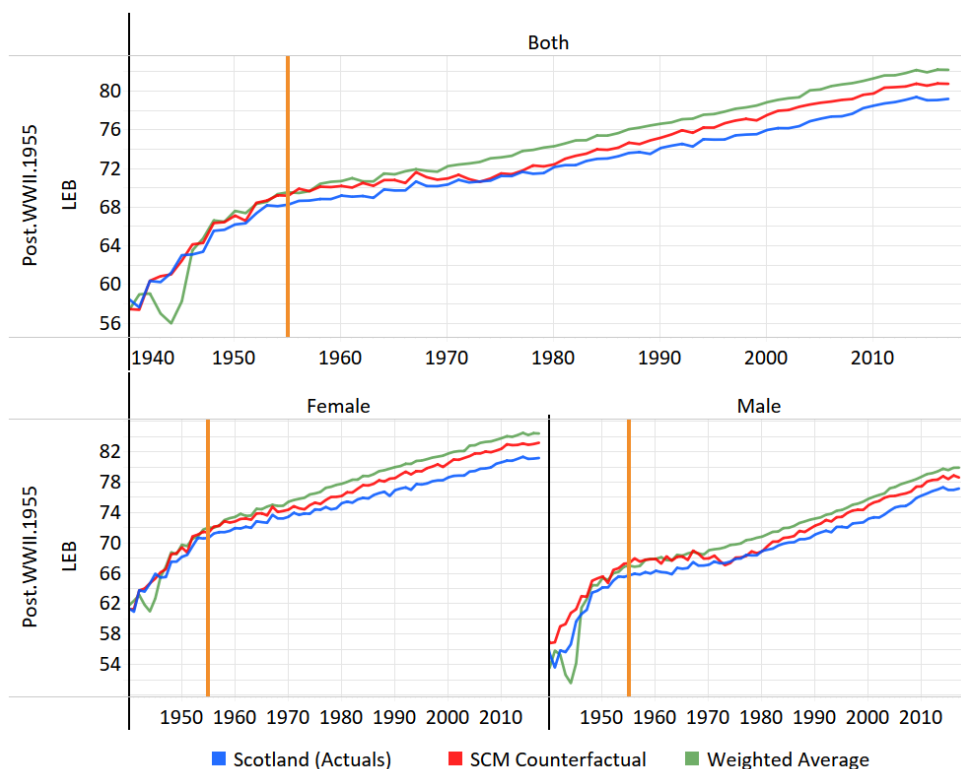
Figure 1.9: Counterfactual, Weighted Average, and Actual Scotland Trends for the Post-WWII (1946 Breakpoint) SCM, 1920 – 2017



Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Post-WWII model (1946 breakpoint). The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1920 to 2017.

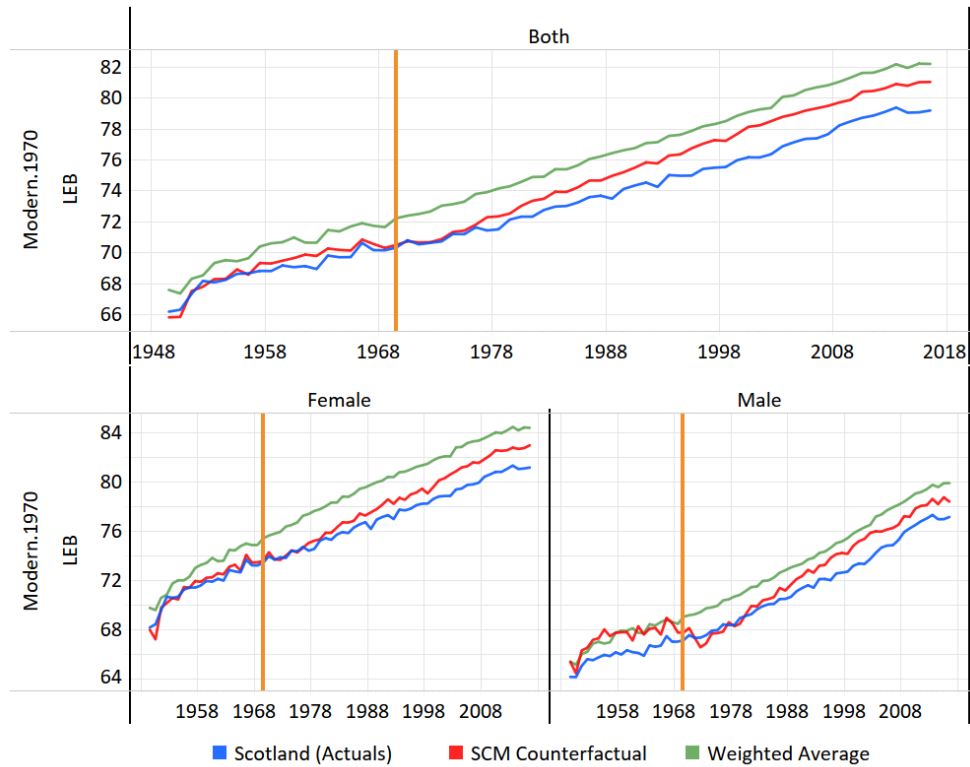
By 1955, the counterfactual was similar at 1.6 years. However, increases in life expectancy began to accelerate by the 1970s, and the counterfactuals began to increase again. The 1970 and 1980, all-age LEB models suggest that, had Scotland met the trend of the weighted countries, lifespans could have been 1.8 or 1.9 years longer (about 81 years) respectively. [See Figure 1.10, Figure 1.11, and Figure 1.12 below.]

Figure 1.10: Counterfactual, Weighted Average, and Actual Scotland Trends for the Post-WWII (1955 Breakpoint) SCM, 1940 – 2017



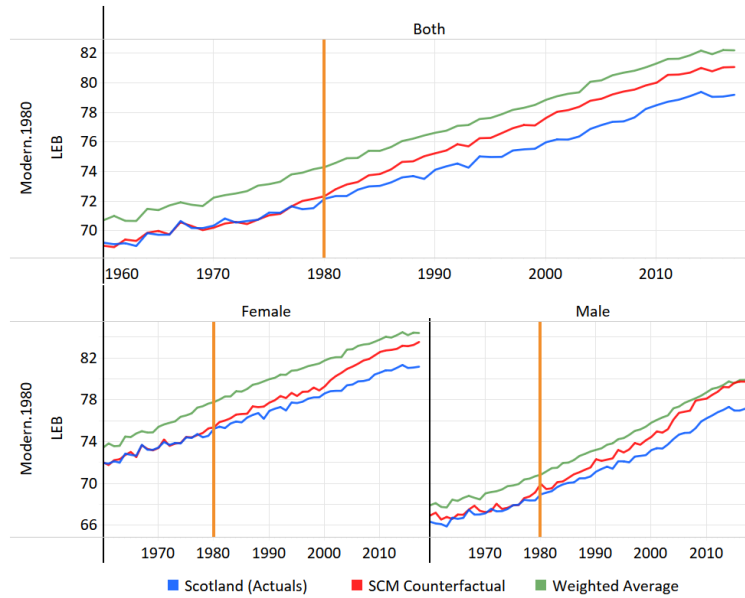
Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Post-WWII model (1955 breakpoint). The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1940 to 2017.

Figure 1.11: Counterfactual, Weighted Average, and Actual Scotland Trends for the Modern (1970 Breakpoint)
SCM, 1950 – 2017



Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Modern model (1970 breakpoint). The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1950 to 2017.

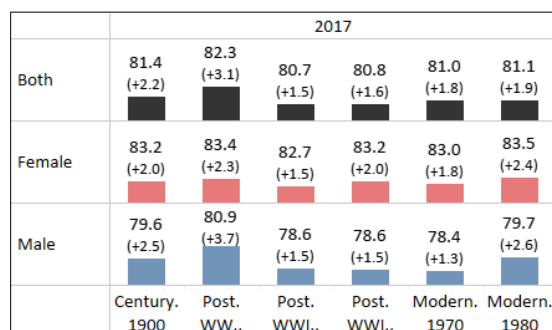
Figure 1.12: Counterfactual, Weighted Average, and Actual Scotland Trends for the Modern (1980 Breakpoint) SCM, 1960 – 2017



Note: Each panel shows life expectancy at birth over time for Scotland (actual), the weighted average for the included countries, and the synthetic control counterfactual for the Modern model (1980 breakpoint). The top panel depicts the total population, and the bottom panels show male and female trends. The plotted years range from 1960 to 2017.

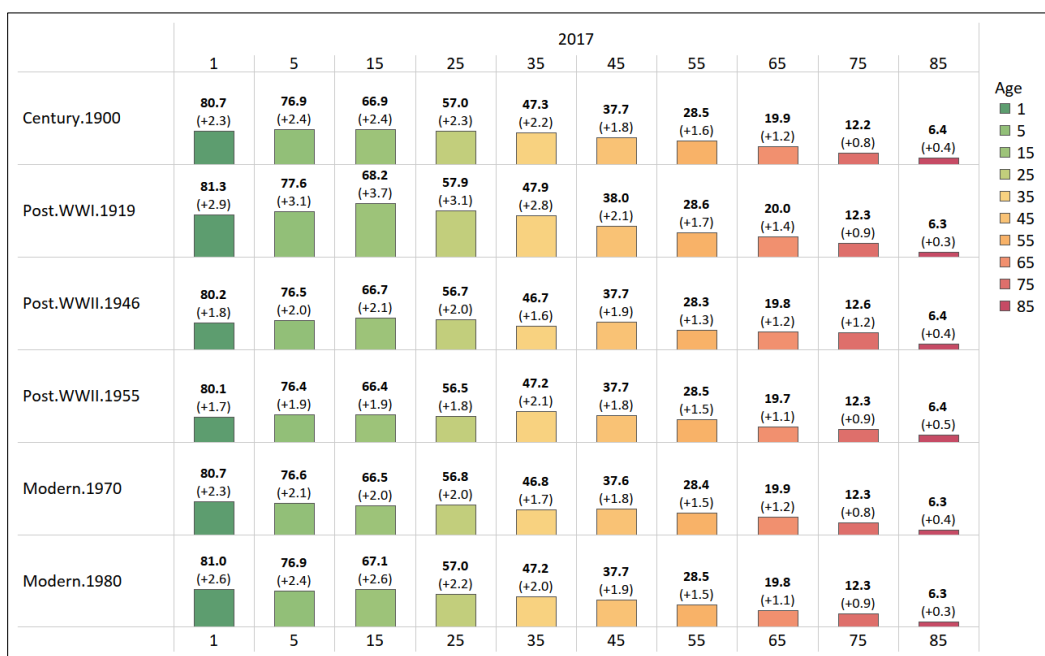
For the 1946, 1955, 1970, and 1980 breakpoint models, demographic results are consistent. As the female-specific life expectancy divergence quickly outpaced the male divergence, the counterfactual-actual difference result flips; counterfactual female life expectancy gains are greater than for males. Across the four models, the magnitude difference by sex increases as the divergence continues. This is summarised in Figure 1.13. Additionally, there is some shifting in the age bracket that would have most benefited if the counterfactual was met. Some models assign the greatest value to infants and children and others to the younger working-class individuals. This is summarised in Figure 1.14. [Note that all model results are summarised in Figure 1.16 and Figure 1.17 in the appendix as well.]

Figure 1.13: 2017 Comparative Counterfactual Results by Sex for each Breakpoint



Note: This bar chart shows predicted life expectancy at birth in 2017 for each sex (rows) and breakpoint model (columns). Each bar displays the predicted counterfactual value at the top and the difference from the actual value in parentheses below (positive values indicate a shortfall between actual and predicted). This allows direct comparison of the scale of divergence across models and sexes.

Figure 1.14: 2017 Comparative Counterfactual Results by Age for each Breakpoint



Note: This bar chart presents 2017 predicted life expectancy for each examined age band (1, 5, 15, ..., 85) across all six breakpoint models. The layout mirrors Figure 15 but aggregates across sexes, focusing on age-specific differences. This highlights how the scale of Scotland's divergence varies across age groups. Colour is based on age.

While this study is not designed to identify a definitive causal mechanism, the timing and consistency of the breakpoint results help discipline which explanations are historically plausible. Across the major recovery

episodes modeled here, most notably the post-World War I and post-World War II decades, Scotland's life expectancy increases, but the gains are persistently flatter than those implied by its synthetic counterfactuals, suggesting weaker recovery dynamics rather than a one-time collapse. One plausible interpretation is that Scotland captured smaller improvements from the mid-twentieth-century reconstruction era than many comparator countries. Economic history evidence indicates that the United Kingdom's post-war catch-up performance lagged leading continental peers in part because of weaker capital deepening and lower investment intensity, conditions that could plausibly limit the pace at which health-enhancing material improvements diffuse. Complementing this macro context, public-health evidence shows that interventions linked to material conditions—such as rehousing, refurbishment, and energy-efficiency measures—can generate measurable health gains, providing a concrete pathway through which uneven post-war investment could translate into persistent differences in mortality improvement.

7 Extensions and Conclusion

Analyzing long-term historical data clarifies when Scotland diverged from other Western countries. It permits research to focus on specific timeframes or to frame causal inference in a historic context. Our models suggests that Scotland was already on a trajectory for a shorter lifespan well before WWII. While some have noted that Scotland's disadvantage extends throughout the 20th and 21st century (see, e.g. Mackenbach, 2013), most have concluded that the Scottish Divergence occurred several decades later. Still, public health and lifespan are functions of many factors that can change over time. Some of these factors are more elastic to mitigation and policy responses; others are less elastic and can have multi-generational consequences. The Divergence has likely ebbed and flowed as new policies, preferences, environments and economies have changed. We see evidence that a second divergence (or re-emergence) occurred near 1970.

Trend analysis, SCMs and other counterfactual modelling aid in identifying when the Scottish Divergence first emerged. Still, there is more to explore. Specifically, WWI mortality impacts the country weights so

dramatically, exploring a non-wartime model may help us better understand why certain countries are weighted more heavily. Is it just the wartime deaths alone or do other similarities in the pre-break period explain the weighting?

Additionally, counterfactual modelling can also be used to test the impact of specific policies or actions. Focusing on events and policies in the pre-WWII period and in or around 1970. In future extensions, we plan to expand on the foundation of this paper to analyse the drivers behind Scotland's initial and second divergences. Specifically, we plan to:

1. Revisit the impacts of neoliberalism (or Thatcherism/Reaganism) in the 1980s on life expectancies and their ongoing relationship that was first purposed as a driver of the second Scottish Divergence in McCartney et al. (2010).
2. Investigate the impact that the Marshall Plan and other post-WWII recovery actions had on life expectancy globally.
3. Explore historical contextual and environmental factors, such as migration patterns and housing conditions, that originated near WWI explain long-term life expectancy impacts.

Because of the complexities of mortality rates, thoughtful control variables are vital for these models. Finally, the literature exploring the Glasgow Effect is prolific and highly correlated. We plan to extended our long-term analysis to examine to what extent deprivation can explain life expectancy gaps between Glasgow and its nearest neighbours.

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Appendix

Table 1.6: Summary Statistics for Life Expectancy at Various Ages and Sexes

				Mean	Median	Min	Max	StdDev	Var
Austria	Both	All Ages	1950 - 2017	74.56	74.46	64.81	81.64	4.52	20.39
		1	1950 - 2017	74.70	74.22	68.32	80.88	3.65	13.31
		5	1950 - 2017	70.89	70.35	65.09	76.93	3.52	12.41
		15	1950 - 2017	61.06	60.49	55.53	66.99	3.43	11.76
		25	1950 - 2017	51.54	50.95	46.31	57.17	3.28	10.78
		35	1950 - 2017	41.99	41.42	37.10	47.39	3.13	9.83
		45	1950 - 2017	32.69	32.19	28.12	37.75	2.94	8.67
		55	1950 - 2017	23.96	23.53	19.92	28.49	2.70	7.26
		65	1950 - 2017	16.13	15.76	12.74	20.03	2.32	5.40
		75	1950 - 2017	9.58	9.14	7.17	12.60	1.67	2.77
		85	1950 - 2017	4.89	4.66	3.67	6.40	0.80	0.64
	Female	All Ages	1950 - 2017	77.57	77.65	67.28	83.94	4.34	18.86
		1	1950 - 2017	77.60	77.32	70.34	83.17	3.54	12.53
		5	1950 - 2017	73.77	73.44	67.09	79.21	3.42	11.66
		15	1950 - 2017	63.92	63.56	57.53	69.28	3.34	11.15
		25	1950 - 2017	54.17	53.80	48.17	59.40	3.26	10.60
		35	1950 - 2017	44.45	44.05	38.91	49.55	3.14	9.88
		45	1950 - 2017	34.96	34.60	29.81	39.82	2.98	8.88
		55	1950 - 2017	25.91	25.54	21.26	30.39	2.76	7.61
		65	1950 - 2017	17.50	17.08	13.54	21.52	2.44	5.95
		75	1950 - 2017	10.25	9.81	7.50	13.49	1.79	3.20
		85	1950 - 2017	5.10	4.85	3.73	6.73	0.84	0.71
	Male	All Ages	1950 - 2017	71.30	70.89	62.18	79.28	4.73	22.34
		1	1950 - 2017	71.52	70.73	66.00	78.52	3.83	14.66
		5	1950 - 2017	67.72	66.88	62.72	74.59	3.71	13.74
		15	1950 - 2017	57.91	57.03	53.22	64.65	3.60	12.98
		25	1950 - 2017	48.58	47.67	44.15	54.89	3.40	11.57
		35	1950 - 2017	39.18	38.32	35.04	45.19	3.22	10.38
		45	1950 - 2017	30.02	29.26	26.18	35.63	3.00	9.00
		55	1950 - 2017	21.56	20.89	18.33	26.49	2.70	7.29
		65	1950 - 2017	14.28	13.75	11.59	18.32	2.23	4.99
		75	1950 - 2017	8.46	7.94	6.73	11.41	1.50	2.24
Canada	Both	All Ages	1925 - 2017	74.26	75.07	57.94	82.06	5.76	33.13
		1	1925 - 2017	74.74	74.87	63.22	81.43	4.41	19.46
		5	1925 - 2017	71.05	71.04	61.32	77.49	4.08	16.63
		15	1925 - 2017	61.34	61.25	52.63	67.56	3.85	14.84
		25	1925 - 2017	51.87	51.80	44.26	57.83	3.62	13.10
		35	1925 - 2017	42.41	42.26	35.93	48.21	3.39	11.52
		45	1925 - 2017	33.15	32.93	27.71	38.67	3.13	9.80
		55	1925 - 2017	24.47	24.30	19.85	29.47	2.77	7.65
		65	1925 - 2017	16.77	16.74	12.88	20.95	2.25	5.06
		75	1925 - 2017	10.38	10.54	7.57	13.39	1.58	2.51
		85	1925 - 2017	5.69	5.96	4.19	7.30	0.83	0.69
	Female	All Ages	1925 - 2017	77.07	78.72	59.14	84.13	5.92	35.10
		1	1925 - 2017	77.42	78.46	63.78	83.47	4.68	21.91
		5	1925 - 2017	73.71	74.61	61.77	79.52	4.34	18.82
		15	1925 - 2017	63.95	64.78	53.03	69.58	4.12	16.98
		25	1925 - 2017	54.32	55.08	44.66	59.77	3.87	14.98
		35	1925 - 2017	44.74	45.38	36.46	50.02	3.58	12.81
		45	1925 - 2017	35.36	35.90	28.33	40.36	3.27	10.69
		55	1925 - 2017	26.45	26.98	20.39	31.02	2.93	8.56
		65	1925 - 2017	18.29	18.80	13.29	22.24	2.47	6.08
		75	1925 - 2017	11.29	11.72	7.83	14.32	1.79	3.21
		85	1925 - 2017	6.09	6.43	4.39	7.82	0.93	0.87
	Male	All Ages	1925 - 2017	71.58	71.60	56.73	79.97	5.53	30.58
		1	1925 - 2017	72.19	71.45	62.71	79.35	4.13	17.08
		5	1925 - 2017	68.52	67.64	60.92	75.41	3.82	14.61
		15	1925 - 2017	58.84	57.88	52.28	65.49	3.60	12.93
		25	1925 - 2017	49.53	48.65	43.92	55.83	3.36	11.29
		35	1925 - 2017	40.17	39.25	35.47	46.32	3.18	10.13
		45	1925 - 2017	31.00	30.03	27.16	36.90	2.96	8.74
		55	1925 - 2017	22.50	21.63	19.36	27.82	2.57	6.62
		65	1925 - 2017	15.15	14.54	12.50	19.50	1.99	3.97
		75	1925 - 2017	9.24	9.04	7.28	12.22	1.29	1.66
		85	1925 - 2017	5.04	5.11	3.89	6.47	0.60	0.36

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				Mean	Median	Min	Max	StdDev	Var
Denmark	Both	All Ages	1860 - 2017	69.9	73.3	39.8	81.1	9.1	82.0
		1	1860 - 2017	71.2	73.3	45.6	80.4	6.7	45.4
		5	1860 - 2017	67.9	69.5	48.8	76.5	5.6	31.6
		15	1860 - 2017	58.5	59.8	43.5	66.5	4.9	23.6
		25	1860 - 2017	49.2	50.2	36.9	56.7	4.2	17.7
		35	1860 - 2017	40.0	40.6	30.4	46.8	3.6	12.7
		45	1860 - 2017	31.0	31.3	23.5	37.2	3.0	8.9
		55	1860 - 2017	22.5	22.7	16.8	28.0	2.5	6.3
		65	1860 - 2017	15.0	15.0	10.9	19.5	2.1	4.3
		75	1860 - 2017	9.0	9.1	6.2	12.1	1.5	2.3
		85	1860 - 2017	4.8	4.8	3.2	6.4	0.9	0.7
	Female	All Ages	1860 - 2017	71.9	75.7	40.8	83.1	9.6	91.2
		1	1860 - 2017	72.9	75.6	46.1	82.4	7.4	55.2
		5	1860 - 2017	69.6	71.8	49.4	78.4	6.3	40.1
		15	1860 - 2017	60.2	62.0	44.8	68.4	5.5	30.7
		25	1860 - 2017	50.8	52.3	37.9	58.5	4.8	23.5
		35	1860 - 2017	41.5	42.6	31.2	48.7	4.1	17.0
		45	1860 - 2017	32.5	33.3	24.5	38.9	3.5	12.2
		55	1860 - 2017	23.9	24.5	17.5	29.6	3.0	9.1
		65	1860 - 2017	16.0	16.4	11.3	20.8	2.5	6.4
		75	1860 - 2017	9.6	9.7	6.4	13.0	1.8	3.4
		85	1860 - 2017	5.0	5.0	3.3	6.9	1.0	1.0
	Male	All Ages	1860 - 2017	67.9	70.8	38.9	79.1	8.6	73.6
		1	1860 - 2017	69.5	71.1	45.0	78.4	6.1	37.4
		5	1860 - 2017	66.2	67.3	48.0	74.5	5.0	24.9
		15	1860 - 2017	56.8	57.6	42.2	64.5	4.3	18.3
		25	1860 - 2017	47.6	48.1	35.8	54.7	3.7	13.4
		35	1860 - 2017	38.4	38.6	29.5	45.0	3.1	9.6
		45	1860 - 2017	29.4	29.4	22.5	35.4	2.6	6.7
		55	1860 - 2017	21.1	20.9	16.0	26.3	2.1	4.4
		65	1860 - 2017	13.9	13.8	10.3	18.1	1.6	2.7
		75	1860 - 2017	8.2	8.2	6.0	11.1	1.1	1.2
		85	1860 - 2017	4.3	4.4	3.0	5.6	0.6	0.4
England and Wales	Both	All Ages	1860 - 2017	68.8	72.1	39.9	81.4	10.8	117.2
		1	1860 - 2017	70.1	72.4	44.2	80.7	8.6	73.3
		5	1860 - 2017	67.2	68.6	44.1	76.8	7.0	48.5
		15	1860 - 2017	57.7	58.8	36.1	66.8	6.3	40.2
		25	1860 - 2017	48.5	49.2	33.4	57.0	5.5	30.8
		35	1860 - 2017	39.4	39.5	28.6	47.3	4.8	22.8
		45	1860 - 2017	30.5	30.2	21.7	37.7	4.1	16.5
		55	1860 - 2017	22.1	21.7	15.3	28.6	3.4	11.3
		65	1860 - 2017	14.8	14.3	9.9	20.0	2.6	6.8
		75	1860 - 2017	8.9	8.7	5.9	12.5	1.7	3.1
		85	1860 - 2017	4.8	4.8	3.3	6.6	0.9	0.8
	Female	All Ages	1860 - 2017	71.4	75.2	41.2	83.2	10.8	117.2
		1	1860 - 2017	72.5	75.4	46.8	82.5	8.7	75.7
		5	1860 - 2017	69.6	71.6	50.1	78.5	7.0	49.5
		15	1860 - 2017	60.1	61.8	43.5	68.6	6.4	40.6
		25	1860 - 2017	50.7	52.0	36.7	58.7	5.7	32.8
		35	1860 - 2017	41.4	42.3	29.8	48.9	5.0	25.1
		45	1860 - 2017	32.4	32.8	22.7	39.3	4.3	18.5
		55	1860 - 2017	23.8	24.1	16.0	30.0	3.6	13.1
		65	1860 - 2017	16.0	16.1	10.4	21.2	2.9	8.2
		75	1860 - 2017	9.6	9.5	6.2	13.3	1.9	3.7
		85	1860 - 2017	5.1	5.0	3.4	7.0	0.9	0.9
	Male	All Ages	1860 - 2017	66.2	68.9	33.4	79.5	10.8	116.8
		1	1860 - 2017	67.7	69.3	36.3	78.9	8.5	71.6
		5	1860 - 2017	64.7	65.6	35.5	74.9	7.0	48.6
		15	1860 - 2017	55.3	55.8	27.0	65.0	6.4	41.1
		25	1860 - 2017	46.2	46.3	26.8	55.2	5.4	29.5
		35	1860 - 2017	37.2	36.7	27.4	45.5	4.6	20.8
		45	1860 - 2017	28.4	27.4	20.6	36.1	3.9	15.0
		55	1860 - 2017	20.2	19.1	14.6	27.1	3.2	10.2
		65	1860 - 2017	13.2	12.3	9.5	18.8	2.4	5.8
		75	1860 - 2017	7.8	7.3	5.6	11.5	1.5	2.4
		85	1860 - 2017	4.2	4.1	3.1	5.9	0.7	0.5

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				Mean	Median	Min	Max	StdDev	Var
Finland	Both	All Ages	1895 - 2017	69.3	71.8	32.8	81.5	10.2	103.2
		1	1895 - 2017	69.9	71.5	36.0	80.7	8.4	70.8
		5	1895 - 2017	66.7	67.7	36.4	76.7	7.3	53.9
		15	1895 - 2017	57.2	58.0	29.1	66.8	6.7	44.9
		25	1895 - 2017	48.2	48.5	27.0	57.0	5.6	31.5
		35	1895 - 2017	39.3	39.0	24.9	47.4	4.7	21.7
		45	1895 - 2017	30.5	30.0	20.8	37.8	4.0	16.2
		55	1895 - 2017	22.2	21.6	15.6	28.6	3.5	12.1
		65	1895 - 2017	14.9	14.3	10.2	20.1	2.8	7.9
		75	1895 - 2017	8.8	8.4	5.8	12.6	1.9	3.7
		85	1895 - 2017	4.6	4.5	3.0	6.5	0.9	0.9
	Female	All Ages	1895 - 2017	73.0	76.1	43.2	84.2	10.1	101.4
		1	1895 - 2017	73.5	75.8	47.8	83.4	8.4	69.8
		5	1895 - 2017	70.2	71.9	49.4	79.4	7.2	51.4
		15	1895 - 2017	60.8	62.1	43.2	69.5	6.4	41.3
		25	1895 - 2017	51.5	52.4	37.2	59.7	5.6	31.6
		35	1895 - 2017	42.3	42.7	31.3	49.8	4.9	23.8
		45	1895 - 2017	33.1	33.2	24.8	40.1	4.3	18.4
		55	1895 - 2017	24.3	24.2	17.8	30.7	3.8	14.5
		65	1895 - 2017	16.2	15.9	11.1	21.8	3.2	10.2
		75	1895 - 2017	9.4	9.1	6.1	13.6	2.2	4.9
		85	1895 - 2017	4.8	4.7	3.0	6.9	1.0	1.1
	Male	All Ages	1895 - 2017	65.6	67.4	26.4	78.7	10.1	103.0
		1	1895 - 2017	66.3	67.2	29.0	77.9	8.4	71.3
		5	1895 - 2017	63.1	63.4	28.6	73.9	7.5	56.2
		15	1895 - 2017	53.6	53.7	20.6	64.0	7.0	48.6
		25	1895 - 2017	44.8	44.3	19.9	54.4	5.7	32.0
		35	1895 - 2017	36.2	35.1	19.9	44.8	4.5	20.2
		45	1895 - 2017	27.6	26.2	17.4	35.4	3.8	14.4
		55	1895 - 2017	19.8	18.5	13.4	26.4	3.2	10.1
		65	1895 - 2017	13.1	12.0	9.1	18.3	2.4	5.7
		75	1895 - 2017	7.8	7.2	5.3	11.2	1.5	2.3
		85	1895 - 2017	4.3	4.3	2.8	5.7	0.7	0.5
France	Both	All Ages	1860 - 2017	67.7	71.5	29.7	82.5	12.5	156.9
		1	1860 - 2017	69.4	72.1	36.1	81.8	9.9	98.8
		5	1860 - 2017	66.5	68.3	38.4	77.8	8.6	73.7
		15	1860 - 2017	57.1	58.6	29.6	67.9	7.9	63.1
		25	1860 - 2017	48.2	49.1	28.4	58.1	6.7	45.3
		35	1860 - 2017	39.5	39.7	25.9	48.4	5.5	30.5
		45	1860 - 2017	30.9	30.6	20.6	38.8	4.7	22.2
		55	1860 - 2017	22.8	22.3	15.0	29.8	4.1	16.5
		65	1860 - 2017	15.4	15.0	9.6	21.5	3.4	11.4
		75	1860 - 2017	9.3	8.9	5.6	13.8	2.4	5.8
		85	1860 - 2017	4.9	4.7	3.0	7.3	1.2	1.6
	Female	All Ages	1860 - 2017	71.2	75.2	32.6	85.5	12.8	163.4
		1	1860 - 2017	72.7	75.6	39.0	84.8	10.3	105.5
		5	1860 - 2017	69.7	71.8	42.7	80.8	8.8	77.6
		15	1860 - 2017	60.3	62.0	37.4	70.9	8.1	65.1
		25	1860 - 2017	51.3	52.3	32.3	61.0	7.1	50.3
		35	1860 - 2017	42.3	42.7	27.1	51.2	6.1	37.5
		45	1860 - 2017	33.3	33.5	21.5	41.5	5.4	28.8
		55	1860 - 2017	24.8	24.7	15.5	32.2	4.7	22.1
		65	1860 - 2017	16.8	16.5	10.0	23.4	3.9	15.2
		75	1860 - 2017	10.0	9.6	5.7	15.0	2.7	7.4
		85	1860 - 2017	5.2	4.9	3.1	7.9	1.4	1.9
	Male	All Ages	1860 - 2017	64.3	67.8	27.3	79.4	12.2	148.2
		1	1860 - 2017	66.2	68.5	30.0	78.8	9.6	91.9
		5	1860 - 2017	63.2	64.8	27.8	74.8	8.4	70.1
		15	1860 - 2017	53.8	55.1	18.6	64.9	7.8	61.6
		25	1860 - 2017	45.1	45.7	19.3	55.2	6.4	41.5
		35	1860 - 2017	36.7	36.5	24.2	45.5	4.9	24.4
		45	1860 - 2017	28.3	27.6	19.8	36.1	4.1	16.5
		55	1860 - 2017	20.5	19.6	14.5	27.3	3.4	11.6
		65	1860 - 2017	13.7	13.0	9.3	19.4	2.8	7.6
		75	1860 - 2017	8.1	7.8	5.4	12.2	1.9	3.7
		85	1860 - 2017	4.3	4.1	2.7	6.3	1.0	0.9

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				Mean	Median	Min	Max	StdDev	Var
Ireland	Both	All Ages	1950 - 2017	74.4	73.6	64.8	81.9	4.1	16.8
		1	1950 - 2017	74.3	73.3	66.8	81.2	3.5	12.0
		5	1950 - 2017	70.5	69.4	63.4	77.2	3.4	11.2
		15	1950 - 2017	60.7	59.6	53.9	67.2	3.3	10.7
		25	1950 - 2017	51.0	50.0	44.7	57.4	3.2	10.3
		35	1950 - 2017	41.4	40.3	35.8	47.7	3.1	9.8
		45	1950 - 2017	32.0	30.9	27.0	38.0	3.0	8.9
		55	1950 - 2017	23.3	22.2	19.0	28.7	2.7	7.1
		65	1950 - 2017	15.5	14.7	12.0	20.0	2.2	4.7
		75	1950 - 2017	9.2	8.8	6.7	12.2	1.4	2.1
		85	1950 - 2017	4.9	4.8	3.7	6.3	0.7	0.5
	Female	All Ages	1950 - 2017	76.8	76.6	66.1	83.7	4.2	17.3
		1	1950 - 2017	76.7	76.3	67.7	83.0	3.6	12.6
		5	1950 - 2017	72.9	72.4	64.4	79.0	3.4	11.8
		15	1950 - 2017	63.0	62.5	54.8	69.0	3.4	11.3
		25	1950 - 2017	53.2	52.7	45.6	59.1	3.3	10.8
		35	1950 - 2017	43.5	42.9	36.7	49.3	3.2	10.0
		45	1950 - 2017	34.0	33.3	28.0	39.6	3.0	8.9
		55	1950 - 2017	25.1	24.4	19.7	30.1	2.7	7.2
		65	1950 - 2017	16.9	16.4	12.5	21.2	2.2	5.0
		75	1950 - 2017	10.1	9.8	7.0	13.1	1.6	2.4
		85	1950 - 2017	5.3	5.2	3.8	6.7	0.7	0.5
	Male	All Ages	1950 - 2017	72.0	70.9	63.5	80.1	4.0	16.0
		1	1950 - 2017	72.1	70.7	65.9	79.3	3.3	11.2
		5	1950 - 2017	68.3	66.8	62.6	75.4	3.2	10.5
		15	1950 - 2017	58.4	57.0	53.0	65.4	3.2	10.0
		25	1950 - 2017	48.9	47.5	43.8	55.7	3.1	9.7
		35	1950 - 2017	39.4	37.9	34.9	46.0	3.1	9.4
		45	1950 - 2017	30.1	28.6	26.1	36.5	2.9	8.6
		55	1950 - 2017	21.5	20.0	18.2	27.3	2.6	6.9
		65	1950 - 2017	14.0	13.0	11.5	18.7	2.1	4.2
		75	1950 - 2017	8.2	7.7	6.4	11.2	1.3	1.6
		85	1950 - 2017	4.4	4.2	3.4	5.8	0.6	0.3
Italy	Both	All Ages	1895 - 2017	70.1	72.8	25.8	83.1	11.1	123.9
		1	1895 - 2017	71.8	73.5	30.5	82.3	8.7	75.5
		5	1895 - 2017	69.0	69.6	34.3	78.3	6.9	47.4
		15	1895 - 2017	59.4	59.9	28.6	68.4	6.3	39.7
		25	1895 - 2017	50.3	50.3	26.6	58.5	5.4	29.0
		35	1895 - 2017	41.1	40.6	25.6	48.7	4.6	21.2
		45	1895 - 2017	32.0	31.3	21.5	39.0	4.0	16.2
		55	1895 - 2017	23.4	22.7	15.8	29.7	3.5	12.3
		65	1895 - 2017	15.6	15.0	9.8	20.9	2.9	8.5
		75	1895 - 2017	9.3	8.8	5.5	13.1	2.1	4.3
		85	1895 - 2017	4.8	4.6	3.0	6.7	1.1	1.1
	Female	All Ages	1895 - 2017	72.7	75.9	28.3	85.2	11.5	132.8
		1	1895 - 2017	74.2	76.5	33.3	84.4	9.1	83.2
		5	1895 - 2017	71.4	72.6	38.1	80.4	7.2	51.9
		15	1895 - 2017	61.9	62.8	33.5	70.5	6.6	43.1
		25	1895 - 2017	52.5	53.0	30.0	60.6	5.8	34.1
		35	1895 - 2017	43.2	43.3	27.2	50.7	5.1	26.4
		45	1895 - 2017	34.0	33.8	22.1	41.0	4.6	20.8
		55	1895 - 2017	25.1	24.8	15.9	31.5	4.1	16.5
		65	1895 - 2017	16.8	16.5	9.7	22.4	3.4	11.8
		75	1895 - 2017	9.9	9.4	5.5	14.1	2.4	5.8
		85	1895 - 2017	5.1	4.8	3.1	7.2	1.2	1.4
	Male	All Ages	1895 - 2017	67.5	69.7	23.5	80.7	10.7	114.5
		1	1895 - 2017	69.2	70.3	27.9	80.0	8.3	68.3
		5	1895 - 2017	66.4	66.5	30.8	76.0	6.6	43.9
		15	1895 - 2017	56.9	56.8	24.2	66.1	6.1	37.4
		25	1895 - 2017	47.9	47.4	23.3	56.3	5.0	24.6
		35	1895 - 2017	38.9	37.9	24.0	46.5	4.1	16.6
		45	1895 - 2017	30.0	28.8	20.9	36.9	3.5	12.2
		55	1895 - 2017	21.6	20.5	15.7	27.6	2.9	8.6
		65	1895 - 2017	14.2	13.4	9.9	19.1	2.3	5.4
		75	1895 - 2017	8.4	7.9	5.5	11.7	1.6	2.6
		85	1895 - 2017	4.4	4.3	2.8	5.9	0.8	0.7

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				Mean	Median	Min	Max	StdDev	Var
Luxembourg	Both	All Ages	1960 - 2017	74.8	74.7	68.6	82.3	4.3	18.7
		1	1960 - 2017	74.6	74.4	69.8	81.6	3.8	14.6
		5	1960 - 2017	70.8	70.5	66.2	77.7	3.7	13.9
		15	1960 - 2017	61.0	60.6	56.5	67.7	3.6	13.3
		25	1960 - 2017	51.4	51.1	47.0	57.8	3.5	12.3
		35	1960 - 2017	41.9	41.7	37.6	48.0	3.4	11.4
		45	1960 - 2017	32.5	32.3	28.4	38.3	3.2	10.1
		55	1960 - 2017	23.8	23.6	20.0	29.0	2.9	8.3
		65	1960 - 2017	16.1	15.9	12.8	20.4	2.4	5.7
		75	1960 - 2017	9.6	9.4	7.2	12.9	1.7	2.9
		85	1960 - 2017	5.0	4.9	3.6	6.6	0.8	0.7
	Female	All Ages	1960 - 2017	78.0	78.2	71.8	84.8	4.0	15.7
		1	1960 - 2017	77.7	77.8	72.6	84.0	3.5	12.3
		5	1960 - 2017	73.8	73.8	69.1	80.1	3.4	11.6
		15	1960 - 2017	64.0	64.0	59.3	70.1	3.3	11.1
		25	1960 - 2017	54.2	54.2	49.6	60.2	3.3	10.8
		35	1960 - 2017	44.5	44.5	40.0	50.3	3.2	10.2
		45	1960 - 2017	35.0	35.1	30.7	40.6	3.0	9.2
		55	1960 - 2017	26.0	26.0	22.0	31.0	2.8	7.8
		65	1960 - 2017	17.6	17.6	13.9	22.0	2.5	6.2
		75	1960 - 2017	10.4	10.3	7.6	14.0	1.8	3.4
		85	1960 - 2017	5.3	5.1	3.8	7.3	0.9	0.9
	Male	All Ages	1960 - 2017	71.7	71.1	65.4	79.8	4.6	21.3
		1	1960 - 2017	71.6	70.8	66.9	79.2	4.1	16.5
		5	1960 - 2017	67.8	66.9	63.1	75.3	4.0	15.8
		15	1960 - 2017	58.0	57.1	53.4	65.3	3.9	15.1
		25	1960 - 2017	48.6	47.8	44.2	55.5	3.7	13.5
		35	1960 - 2017	39.1	38.5	34.8	45.7	3.5	12.4
		45	1960 - 2017	29.9	29.3	25.9	36.2	3.3	10.9
		55	1960 - 2017	21.5	20.8	17.8	27.0	2.9	8.7
		65	1960 - 2017	14.2	13.7	11.3	18.6	2.3	5.3
		75	1960 - 2017	8.5	8.0	6.5	11.6	1.5	2.2
		85	1960 - 2017	4.5	4.4	3.2	5.9	0.6	0.4
Netherlands	Both	All Ages	1860 - 2017	70.2	73.7	33.0	81.7	11.0	120.0
		1	1860 - 2017	71.5	73.7	41.2	81.0	8.1	65.8
		5	1860 - 2017	68.6	70.0	44.7	77.1	6.5	42.2
		15	1860 - 2017	59.2	60.3	39.6	67.1	5.8	33.3
		25	1860 - 2017	49.9	50.6	33.0	57.3	5.0	25.5
		35	1860 - 2017	40.6	41.0	27.1	47.5	4.3	18.6
		45	1860 - 2017	31.6	31.6	21.6	37.8	3.6	13.2
		55	1860 - 2017	23.0	22.9	15.6	28.5	3.1	9.4
		65	1860 - 2017	15.3	15.1	10.3	19.9	2.5	6.0
		75	1860 - 2017	9.1	9.0	5.9	12.3	1.7	2.9
		85	1860 - 2017	4.8	4.7	3.1	6.3	0.9	0.7
	Female	All Ages	1860 - 2017	72.3	76.5	34.0	83.3	11.4	130.4
		1	1860 - 2017	73.4	76.3	41.8	82.6	8.8	77.4
		5	1860 - 2017	70.4	72.6	45.4	78.6	7.2	51.8
		15	1860 - 2017	61.0	62.8	40.3	68.7	6.5	41.8
		25	1860 - 2017	51.6	53.0	33.4	58.8	5.8	33.3
		35	1860 - 2017	42.3	43.3	27.5	48.9	5.0	25.0
		45	1860 - 2017	33.2	33.8	22.1	39.2	4.3	18.2
		55	1860 - 2017	24.4	24.8	15.9	29.9	3.7	13.7
		65	1860 - 2017	16.4	16.5	10.3	21.2	3.0	9.3
		75	1860 - 2017	9.7	9.5	6.0	13.2	2.1	4.3
		85	1860 - 2017	5.0	4.9	3.2	6.7	1.0	1.0
	Male	All Ages	1860 - 2017	68.1	71.3	32.1	80.1	10.5	110.0
		1	1860 - 2017	69.7	71.6	40.6	79.4	7.5	55.8
		5	1860 - 2017	66.7	67.9	44.1	75.4	5.9	34.3
		15	1860 - 2017	57.3	58.3	39.0	65.5	5.2	26.6
		25	1860 - 2017	48.1	48.9	32.7	55.7	4.4	19.3
		35	1860 - 2017	38.9	39.3	26.7	46.0	3.7	13.8
		45	1860 - 2017	29.9	29.9	21.0	36.3	3.1	9.6
		55	1860 - 2017	21.4	21.3	15.4	27.1	2.5	6.3
		65	1860 - 2017	14.0	14.0	10.2	18.6	1.9	3.6
		75	1860 - 2017	8.2	8.3	5.8	11.2	1.2	1.5
		85	1860 - 2017	4.4	4.5	3.0	5.6	0.6	0.4

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				Mean	Median	Min	Max	StdDev	Var
Northern Ireland	Both	All Ages	1925 - 2017	72.23	71.86	54.40	80.57	6.13	37.64
		1	1925 - 2017	72.77	72.41	58.54	79.96	4.82	23.19
		5	1925 - 2017	69.13	68.65	57.58	76.01	4.35	18.92
		15	1925 - 2017	59.40	58.83	48.97	66.09	4.11	16.87
		25	1925 - 2017	49.92	49.20	41.01	56.35	3.84	14.71
		35	1925 - 2017	40.47	39.60	32.84	46.71	3.55	12.63
		45	1925 - 2017	31.26	30.27	24.96	37.21	3.25	10.57
		55	1925 - 2017	22.69	21.70	17.60	28.08	2.84	8.05
		65	1925 - 2017	15.19	14.50	11.26	19.61	2.27	5.17
		75	1925 - 2017	9.20	8.77	6.66	12.18	1.49	2.23
		85	1925 - 2017	5.02	4.91	3.76	6.51	0.74	0.54
	Female	All Ages	1925 - 2017	74.62	75.20	54.74	82.44	6.52	42.52
		1	1925 - 2017	75.03	75.27	58.19	81.74	5.32	28.29
		5	1925 - 2017	71.38	71.48	57.17	77.78	4.83	23.35
		15	1925 - 2017	61.62	61.67	48.70	67.86	4.57	20.91
		25	1925 - 2017	51.99	51.95	40.83	58.02	4.22	17.83
		35	1925 - 2017	42.45	42.25	32.77	48.24	3.84	14.73
		45	1925 - 2017	33.14	32.77	25.04	38.56	3.46	11.97
		55	1925 - 2017	24.37	23.96	17.75	29.34	3.03	9.16
		65	1925 - 2017	16.45	16.18	11.36	20.64	2.48	6.14
		75	1925 - 2017	9.93	9.69	6.84	12.87	1.66	2.76
		85	1925 - 2017	5.33	5.26	3.87	6.82	0.79	0.62
	Male	All Ages	1925 - 2017	69.78	68.95	54.12	78.75	5.75	33.12
		1	1925 - 2017	70.43	69.40	58.91	78.10	4.37	19.11
		5	1925 - 2017	66.80	65.58	58.01	74.17	3.94	15.56
		15	1925 - 2017	57.10	55.83	49.27	64.25	3.73	13.88
		25	1925 - 2017	47.74	46.27	41.21	54.61	3.52	12.37
		35	1925 - 2017	38.38	36.84	32.92	45.11	3.34	11.12
		45	1925 - 2017	29.23	27.55	24.83	35.73	3.11	9.68
		55	1925 - 2017	20.83	19.42	17.42	26.71	2.72	7.38
		65	1925 - 2017	13.68	12.68	10.99	18.38	2.10	4.42
		75	1925 - 2017	8.17	7.60	6.43	11.28	1.29	1.66
		85	1925 - 2017	4.41	4.23	3.46	5.93	0.60	0.36
Norway	Both	All Ages	1860 - 2017	71.36	74.07	44.71	82.63	9.07	82.34
		1	1860 - 2017	71.94	74.02	49.47	81.81	7.61	57.85
		5	1860 - 2017	68.84	70.36	50.89	77.86	6.34	40.14
		15	1860 - 2017	59.44	60.65	42.98	67.91	5.59	31.21
		25	1860 - 2017	50.43	51.02	38.31	58.11	4.62	21.32
		35	1860 - 2017	41.41	41.49	32.32	48.34	3.72	13.83
		45	1860 - 2017	32.44	32.16	25.21	38.64	3.03	9.17
		55	1860 - 2017	23.85	23.35	18.16	29.25	2.47	6.10
		65	1860 - 2017	16.05	15.47	11.86	20.46	1.95	3.78
		75	1860 - 2017	9.58	9.10	7.11	12.68	1.32	1.75
		85	1860 - 2017	5.01	4.77	3.78	6.49	0.65	0.43
	Female	All Ages	1860 - 2017	73.72	76.94	45.80	84.28	9.50	90.30
		1	1860 - 2017	74.16	76.87	50.27	83.47	8.13	66.14
		5	1860 - 2017	71.01	73.12	52.47	79.50	6.88	47.36
		15	1860 - 2017	61.60	63.30	44.73	69.56	6.10	37.16
		25	1860 - 2017	52.37	53.49	39.62	59.66	5.19	26.97
		35	1860 - 2017	43.20	43.74	33.14	49.81	4.29	18.36
		45	1860 - 2017	34.11	34.20	26.09	40.06	3.54	12.50
		55	1860 - 2017	25.32	25.07	18.63	30.59	2.95	8.72
		65	1860 - 2017	17.16	16.65	12.19	21.58	2.38	5.68
		75	1860 - 2017	10.20	9.69	7.38	13.53	1.63	2.65
		85	1860 - 2017	5.25	4.95	3.84	6.93	0.76	0.58
	Male	All Ages	1860 - 2017	69.02	71.36	43.61	80.92	8.69	75.48
		1	1860 - 2017	69.73	71.77	48.61	80.10	7.15	51.05
		5	1860 - 2017	66.66	68.05	49.24	76.15	5.87	34.47
		15	1860 - 2017	57.28	58.29	41.18	66.20	5.16	26.67
		25	1860 - 2017	48.45	48.96	36.90	56.49	4.13	17.07
		35	1860 - 2017	39.58	39.52	31.45	46.79	3.25	10.59
		45	1860 - 2017	30.70	30.39	24.28	37.14	2.63	6.94
		55	1860 - 2017	22.29	21.84	17.62	27.81	2.10	4.41
		65	1860 - 2017	14.81	14.41	11.46	19.19	1.57	2.45
		75	1860 - 2017	8.76	8.53	6.75	11.61	0.97	0.95
		85	1860 - 2017	4.59	4.55	3.56	5.82	0.44	0.20

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				Mean	Median	Min	Max	StdDev	Var
Poland	Both	All Ages	1960 - 2017	72.13	70.92	67.63	77.80	2.84	8.08
		1	1960 - 2017	72.64	71.67	70.44	77.13	1.99	3.94
		5	1960 - 2017	68.82	67.94	66.82	73.17	1.90	3.62
		15	1960 - 2017	59.00	58.13	57.00	63.24	1.84	3.40
		25	1960 - 2017	49.42	48.58	47.46	53.50	1.77	3.14
		35	1960 - 2017	39.97	39.22	38.09	43.87	1.67	2.78
		45	1960 - 2017	30.90	30.19	29.25	34.51	1.55	2.40
		55	1960 - 2017	22.56	21.81	20.99	25.85	1.46	2.14
		65	1960 - 2017	15.23	14.59	13.59	18.25	1.39	1.93
		75	1960 - 2017	9.17	8.72	7.85	11.64	1.09	1.18
		85	1960 - 2017	4.89	4.65	4.15	6.20	0.54	0.30
	Female	All Ages	1960 - 2017	76.05	75.15	70.53	81.72	3.12	9.71
		1	1960 - 2017	76.42	75.58	73.00	81.02	2.26	5.12
		5	1960 - 2017	72.60	71.75	69.43	77.06	2.17	4.69
		15	1960 - 2017	62.75	61.89	59.69	67.12	2.11	4.47
		25	1960 - 2017	52.97	52.09	50.05	57.25	2.06	4.24
		35	1960 - 2017	43.26	42.38	40.58	47.42	1.97	3.87
		45	1960 - 2017	33.82	33.00	31.33	37.76	1.86	3.45
		55	1960 - 2017	24.91	24.14	22.57	28.56	1.75	3.06
		65	1960 - 2017	16.75	16.14	14.59	20.13	1.62	2.62
		75	1960 - 2017	9.87	9.46	8.30	12.59	1.21	1.47
		85	1960 - 2017	5.08	4.86	4.30	6.46	0.58	0.33
	Male	All Ages	1960 - 2017	68.20	66.88	64.55	73.85	2.65	7.03
		1	1960 - 2017	68.79	68.13	66.23	73.19	1.86	3.46
		5	1960 - 2017	64.99	64.45	62.39	69.24	1.80	3.22
		15	1960 - 2017	55.19	54.74	52.58	59.31	1.74	3.03
		25	1960 - 2017	45.77	45.41	43.23	49.66	1.66	2.76
		35	1960 - 2017	36.53	36.25	34.11	40.21	1.55	2.41
		45	1960 - 2017	27.74	27.45	25.64	31.06	1.40	1.95
		55	1960 - 2017	19.85	19.38	18.30	22.80	1.24	1.54
		65	1960 - 2017	13.21	12.67	11.77	15.86	1.14	1.30
		75	1960 - 2017	8.00	7.58	6.90	10.11	0.89	0.79
		85	1960 - 2017	4.42	4.22	3.82	5.60	0.46	0.21
Portugal	Both	All Ages	1950 - 2017	72.45	73.64	58.47	81.50	6.13	37.53
		1	1950 - 2017	73.54	73.82	63.69	80.71	4.20	17.67
		5	1950 - 2017	70.21	70.10	62.98	76.76	3.51	12.33
		15	1950 - 2017	60.53	60.37	53.90	66.82	3.32	11.02
		25	1950 - 2017	51.05	50.94	45.17	56.99	3.15	9.93
		35	1950 - 2017	41.66	41.50	36.61	47.24	2.98	8.88
		45	1950 - 2017	32.52	32.28	28.00	37.68	2.80	7.82
		55	1950 - 2017	23.88	23.65	19.80	28.66	2.58	6.67
		65	1950 - 2017	16.00	15.86	12.59	20.23	2.22	4.92
		75	1950 - 2017	9.43	9.36	6.87	12.49	1.56	2.44
		85	1950 - 2017	4.98	4.93	3.62	6.36	0.74	0.54
	Female	All Ages	1950 - 2017	75.70	77.07	61.02	84.38	6.29	39.51
		1	1950 - 2017	76.67	77.16	66.03	83.57	4.42	19.55
		5	1950 - 2017	73.33	73.44	65.36	79.61	3.69	13.59
		15	1950 - 2017	63.61	63.65	56.27	69.67	3.51	12.32
		25	1950 - 2017	53.92	53.95	47.44	59.79	3.37	11.34
		35	1950 - 2017	44.32	44.28	38.71	49.94	3.20	10.23
		45	1950 - 2017	34.92	34.82	29.85	40.27	3.02	9.14
		55	1950 - 2017	25.88	25.75	21.26	30.92	2.81	7.91
		65	1950 - 2017	17.40	17.33	13.52	21.89	2.45	5.99
		75	1950 - 2017	10.18	10.07	7.36	13.51	1.74	3.03
		85	1950 - 2017	5.25	5.18	3.83	6.80	0.81	0.66
	Male	All Ages	1950 - 2017	69.12	70.15	55.78	78.40	5.98	35.75
		1	1950 - 2017	70.29	70.39	61.14	77.63	4.03	16.21
		5	1950 - 2017	66.96	66.68	60.37	73.69	3.38	11.43
		15	1950 - 2017	57.31	56.99	51.29	63.76	3.18	10.10
		25	1950 - 2017	48.01	47.80	42.63	53.98	2.97	8.84
		35	1950 - 2017	38.82	38.57	34.22	44.30	2.79	7.78
		45	1950 - 2017	29.91	29.56	25.88	34.85	2.59	6.73
		55	1950 - 2017	21.62	21.31	18.04	26.12	2.37	5.62
		65	1950 - 2017	14.28	14.08	11.36	18.25	1.99	3.98
		75	1950 - 2017	8.34	8.28	6.13	11.10	1.36	1.85
		85	1950 - 2017	4.41	4.37	3.16	5.60	0.64	0.40

Continue on next page.

				Mean	Median	Min	Max	StdDev	Var
Scotland	Both	All Ages	1860 - 2017	67.0	70.3	40.2	79.4	10.3	106.3
		1	1860 - 2017	68.4	70.7	45.0	78.7	8.2	66.9
		5	1860 - 2017	65.6	67.0	48.7	74.7	6.4	41.3
		15	1860 - 2017	56.2	57.2	42.7	64.8	5.7	32.1
		25	1860 - 2017	47.1	47.6	35.9	55.0	4.9	24.2
		35	1860 - 2017	38.0	38.0	28.8	45.3	4.2	17.6
		45	1860 - 2017	29.2	28.8	21.9	36.0	3.5	12.5
		55	1860 - 2017	21.1	20.6	15.5	27.0	2.9	8.4
		65	1860 - 2017	14.1	13.6	10.2	18.8	2.2	4.9
		75	1860 - 2017	8.5	8.2	6.1	11.6	1.5	2.3
		85	1860 - 2017	4.7	4.5	3.4	6.2	0.8	0.6
	Female	All Ages	1860 - 2017	69.4	73.4	41.5	81.3	10.7	114.6
		1	1860 - 2017	70.6	73.7	46.0	80.6	8.8	76.6
		5	1860 - 2017	67.8	69.9	49.5	76.6	7.0	48.7
		15	1860 - 2017	58.4	60.1	43.3	66.7	6.2	38.3
		25	1860 - 2017	49.1	50.3	36.7	56.8	5.4	29.1
		35	1860 - 2017	40.0	40.7	29.8	47.1	4.6	20.8
		45	1860 - 2017	31.1	31.4	23.0	37.5	3.8	14.6
		55	1860 - 2017	22.7	22.9	16.2	28.4	3.2	10.0
		65	1860 - 2017	15.2	15.2	10.6	19.9	2.4	6.0
		75	1860 - 2017	9.1	8.9	6.3	12.3	1.7	2.8
		85	1860 - 2017	4.9	4.8	3.5	6.5	0.8	0.7
	Male	All Ages	1860 - 2017	64.4	67.1	38.8	77.3	9.9	98.3
		1	1860 - 2017	66.0	67.7	43.8	76.6	7.6	58.4
		5	1860 - 2017	63.2	63.9	47.5	72.7	5.9	35.3
		15	1860 - 2017	53.9	54.2	41.3	62.7	5.2	27.3
		25	1860 - 2017	44.8	44.7	34.8	53.0	4.5	20.2
		35	1860 - 2017	35.9	35.2	27.7	43.5	3.9	15.0
		45	1860 - 2017	27.2	26.1	20.8	34.3	3.3	10.9
		55	1860 - 2017	19.3	18.2	14.7	25.6	2.7	7.3
		65	1860 - 2017	12.6	11.7	9.6	17.5	2.0	4.1
		75	1860 - 2017	7.5	7.0	5.8	10.8	1.3	1.7
		85	1860 - 2017	4.1	3.9	3.2	5.7	0.7	0.4
Spain	Both	All Ages	1925 - 2017	72.4	75.5	47.0	83.1	9.4	87.7
		1	1925 - 2017	73.5	75.4	53.1	82.3	7.2	52.5
		5	1925 - 2017	70.2	71.6	53.2	78.3	6.1	36.7
		15	1925 - 2017	60.6	61.8	45.0	68.4	5.6	31.5
		25	1925 - 2017	51.2	52.2	37.9	58.5	5.0	25.4
		35	1925 - 2017	41.9	42.6	30.5	48.7	4.5	19.9
		45	1925 - 2017	32.8	33.3	23.0	39.0	4.0	15.7
		55	1925 - 2017	24.2	24.4	16.1	29.7	3.5	12.0
		65	1925 - 2017	16.3	16.4	10.3	21.1	2.9	8.1
		75	1925 - 2017	9.8	9.7	5.8	13.3	1.9	3.7
		85	1925 - 2017	5.3	5.1	3.4	6.9	0.8	0.7
	Female	All Ages	1925 - 2017	75.4	78.6	48.5	85.8	9.5	90.1
		1	1925 - 2017	76.3	78.4	54.3	85.0	7.4	55.2
		5	1925 - 2017	73.1	74.5	56.7	81.0	6.2	38.6
		15	1925 - 2017	63.4	64.7	48.7	71.1	5.8	33.3
		25	1925 - 2017	53.9	54.9	41.1	61.1	5.3	27.7
		35	1925 - 2017	44.5	45.2	33.5	51.3	4.8	22.6
		45	1925 - 2017	35.1	35.6	25.8	41.5	4.3	18.5
		55	1925 - 2017	26.1	26.5	18.1	32.0	3.9	14.8
		65	1925 - 2017	17.7	17.9	11.4	23.0	3.2	10.4
		75	1925 - 2017	10.6	10.5	6.4	14.4	2.2	4.6
		85	1925 - 2017	5.6	5.3	3.6	7.3	0.9	0.8
	Male	All Ages	1925 - 2017	69.4	72.4	42.9	80.3	9.2	84.9
		1	1925 - 2017	70.6	72.4	48.8	79.6	7.1	50.0
		5	1925 - 2017	67.3	68.6	48.8	75.6	5.9	35.1
		15	1925 - 2017	57.7	58.8	40.6	65.7	5.5	30.2
		25	1925 - 2017	48.4	49.3	34.0	55.8	4.8	23.5
		35	1925 - 2017	39.3	39.9	27.2	46.1	4.2	17.5
		45	1925 - 2017	30.3	30.6	20.2	36.4	3.6	13.1
		55	1925 - 2017	22.0	22.1	14.1	27.3	3.1	9.4
		65	1925 - 2017	14.6	14.6	9.1	19.1	2.5	6.0
		75	1925 - 2017	8.7	8.6	5.1	11.8	1.7	2.7
		85	1925 - 2017	4.7	4.6	2.9	6.2	0.7	0.5

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				Mean	Median	Min	Max	StdDev	Var
Sweden	Both	All Ages	1860 - 2017	71.42	74.15	41.01	82.44	9.59	91.93
		1	1860 - 2017	72.16	74.09	47.13	81.63	7.70	59.33
		5	1860 - 2017	68.96	70.25	50.51	77.67	6.44	41.52
		15	1860 - 2017	59.56	60.46	42.87	67.72	5.66	32.07
		25	1860 - 2017	50.38	50.88	37.54	57.93	4.91	24.07
		35	1860 - 2017	41.23	41.28	30.19	48.22	4.18	17.47
		45	1860 - 2017	32.19	31.96	23.07	38.55	3.55	12.61
		55	1860 - 2017	23.57	23.12	16.37	29.14	2.98	8.89
		65	1860 - 2017	15.75	15.17	10.36	20.36	2.40	5.74
		75	1860 - 2017	9.28	8.81	5.86	12.54	1.68	2.81
		85	1860 - 2017	4.79	4.57	3.15	6.38	0.85	0.72
	Female	All Ages	1860 - 2017	73.44	76.63	42.72	84.12	9.98	99.65
		1	1860 - 2017	74.02	76.41	48.52	83.31	8.24	67.97
		5	1860 - 2017	70.79	72.54	51.93	79.35	7.01	49.17
		15	1860 - 2017	61.38	62.71	44.45	69.40	6.22	38.69
		25	1860 - 2017	52.08	52.93	38.89	59.52	5.46	29.77
		35	1860 - 2017	42.84	43.27	31.50	49.69	4.70	22.06
		45	1860 - 2017	33.71	33.79	24.27	39.92	4.04	16.34
		55	1860 - 2017	24.92	24.73	17.09	30.43	3.47	12.07
		65	1860 - 2017	16.79	16.39	10.82	21.48	2.86	8.18
		75	1860 - 2017	9.90	9.41	6.13	13.41	2.00	4.02
		85	1860 - 2017	5.05	4.81	3.35	6.81	0.98	0.96
	Male	All Ages	1860 - 2017	69.41	71.85	39.32	80.73	9.23	85.15
		1	1860 - 2017	70.31	71.90	45.71	79.92	7.22	52.18
		5	1860 - 2017	67.12	68.07	49.07	75.95	5.95	35.39
		15	1860 - 2017	57.73	58.31	41.28	66.01	5.19	26.89
		25	1860 - 2017	48.65	48.85	36.09	56.29	4.44	19.74
		35	1860 - 2017	39.59	39.41	28.75	46.69	3.75	14.07
		45	1860 - 2017	30.62	30.17	21.64	37.10	3.15	9.89
		55	1860 - 2017	22.14	21.54	15.16	27.77	2.56	6.55
		65	1860 - 2017	14.60	13.99	9.69	19.14	1.96	3.85
		75	1860 - 2017	8.51	8.12	5.47	11.54	1.30	1.68
		85	1860 - 2017	4.37	4.31	2.75	5.74	0.63	0.39
Switzerland	Both	All Ages	1895 - 2017	72.88	74.79	46.30	83.46	8.28	68.60
		1	1895 - 2017	73.41	74.59	49.79	82.75	6.72	45.10
		5	1895 - 2017	69.85	70.79	47.95	78.78	6.18	38.18
		15	1895 - 2017	60.20	61.01	39.59	68.83	5.84	34.07
		25	1895 - 2017	50.84	51.54	33.73	58.98	5.38	28.99
		35	1895 - 2017	41.51	41.95	29.47	49.18	4.90	24.05
		45	1895 - 2017	32.32	32.57	22.60	39.46	4.43	19.61
		55	1895 - 2017	23.66	23.76	15.64	30.06	3.87	15.00
		65	1895 - 2017	15.90	15.86	9.82	21.26	3.16	9.97
		75	1895 - 2017	9.46	9.36	5.59	13.31	2.17	4.72
		85	1895 - 2017	4.88	4.77	3.04	6.76	1.04	1.09
	Female	All Ages	1895 - 2017	75.45	78.01	48.41	85.37	8.60	73.94
		1	1895 - 2017	75.84	77.71	52.12	84.63	7.17	51.35
		5	1895 - 2017	72.25	73.87	50.45	80.67	6.63	43.95
		15	1895 - 2017	62.57	64.07	42.29	70.72	6.28	39.41
		25	1895 - 2017	53.06	54.35	36.15	60.80	5.78	33.43
		35	1895 - 2017	43.61	44.62	30.85	50.93	5.26	27.62
		45	1895 - 2017	34.29	35.10	23.29	41.15	4.78	22.85
		55	1895 - 2017	25.37	25.98	15.91	31.60	4.28	18.28
		65	1895 - 2017	17.15	17.46	9.76	22.54	3.57	12.74
		75	1895 - 2017	10.14	10.15	5.53	14.18	2.46	6.06
		85	1895 - 2017	5.13	5.03	3.09	7.18	1.14	1.31
	Male	All Ages	1895 - 2017	70.21	71.50	43.76	81.53	7.94	63.10
		1	1895 - 2017	70.87	71.38	47.49	80.80	6.27	39.32
		5	1895 - 2017	67.33	67.60	45.49	76.83	5.74	32.98
		15	1895 - 2017	57.70	57.85	36.95	66.88	5.41	29.29
		25	1895 - 2017	48.48	48.60	31.35	57.07	4.99	24.91
		35	1895 - 2017	39.25	39.13	27.90	47.31	4.55	20.68
		45	1895 - 2017	30.17	29.84	21.77	37.64	4.07	16.57
		55	1895 - 2017	21.73	21.29	15.32	28.34	3.46	11.98
		65	1895 - 2017	14.38	13.89	9.80	19.75	2.70	7.28
		75	1895 - 2017	8.49	8.17	5.51	12.14	1.77	3.14
		85	1895 - 2017	4.41	4.37	2.97	6.02	0.83	0.68

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				Mean	Median	Min	Max	StdDev	Var
United States	Both	All Ages	1935 - 2017	73.48	74.56	60.35	79.05	4.19	17.53
		1	1935 - 2017	73.66	74.39	63.19	78.51	3.44	11.82
		5	1935 - 2017	69.87	70.56	60.32	74.59	3.28	10.78
		15	1935 - 2017	60.09	60.73	51.14	64.67	3.16	9.98
		25	1935 - 2017	50.66	51.25	42.45	55.06	3.03	9.17
		35	1935 - 2017	41.31	41.82	34.01	45.60	2.91	8.45
		45	1935 - 2017	32.23	32.61	25.98	36.37	2.71	7.35
		55	1935 - 2017	23.85	24.12	18.67	27.64	2.38	5.68
		65	1935 - 2017	16.47	16.72	12.28	19.72	1.92	3.70
		75	1935 - 2017	10.32	10.58	7.36	12.63	1.34	1.81
		85	1935 - 2017	5.72	5.98	4.16	7.00	0.69	0.48
	Female	All Ages	1935 - 2017	76.64	78.09	62.60	81.42	4.04	16.34
		1	1935 - 2017	76.72	77.88	65.09	80.86	3.35	11.24
		5	1935 - 2017	72.92	74.04	62.17	76.93	3.19	10.20
		15	1935 - 2017	63.11	64.19	52.91	67.00	3.08	9.50
		25	1935 - 2017	53.46	54.49	44.14	57.22	2.94	8.67
		35	1935 - 2017	43.91	44.84	35.64	47.61	2.78	7.72
		45	1935 - 2017	34.64	35.40	27.42	38.21	2.56	6.56
		55	1935 - 2017	25.92	26.54	19.77	29.24	2.28	5.19
		65	1935 - 2017	17.99	18.58	12.98	20.92	1.93	3.71
		75	1935 - 2017	11.20	11.72	7.76	13.40	1.42	2.03
		85	1935 - 2017	6.09	6.38	4.34	7.36	0.74	0.55
	Male	All Ages	1935 - 2017	70.35	70.97	58.35	76.61	4.26	18.16
		1	1935 - 2017	70.62	70.84	61.50	76.10	3.49	12.15
		5	1935 - 2017	66.84	67.02	58.68	72.18	3.34	11.14
		15	1935 - 2017	57.09	57.22	49.58	62.28	3.21	10.29
		25	1935 - 2017	47.87	47.93	40.97	52.80	3.06	9.39
		35	1935 - 2017	38.68	38.68	32.57	43.52	2.97	8.84
		45	1935 - 2017	29.78	29.61	24.71	34.42	2.79	7.81
		55	1935 - 2017	21.66	21.36	17.68	25.89	2.44	5.97
		65	1935 - 2017	14.73	14.42	11.63	18.34	1.90	3.62
		75	1935 - 2017	9.13	8.95	6.95	11.64	1.22	1.48
		85	1935 - 2017	5.05	5.11	3.93	6.40	0.55	0.31
W.E. Germany	Both	All Ages	1960 - 2017	75.27	75.32	69.24	80.94	3.72	13.85
		1	1960 - 2017	75.09	74.82	70.76	80.21	3.16	10.00
		5	1960 - 2017	71.25	70.91	67.14	76.25	3.07	9.41
		15	1960 - 2017	61.42	61.15	57.42	66.31	2.98	8.88
		25	1960 - 2017	51.81	51.51	47.96	56.47	2.85	8.10
		35	1960 - 2017	42.22	41.91	38.56	46.69	2.72	7.43
		45	1960 - 2017	32.87	32.61	29.37	37.07	2.58	6.65
		55	1960 - 2017	24.11	23.88	20.79	27.94	2.40	5.75
		65	1960 - 2017	16.24	16.14	13.38	19.65	2.11	4.46
		75	1960 - 2017	9.67	9.54	7.50	12.22	1.54	2.37
		85	1960 - 2017	4.99	4.93	3.82	6.22	0.77	0.59
	Female	All Ages	1960 - 2017	78.09	78.37	71.75	83.33	3.65	13.29
		1	1960 - 2017	77.83	77.77	73.03	82.58	3.13	9.81
		5	1960 - 2017	73.98	73.84	69.37	78.63	3.04	9.26
		15	1960 - 2017	64.13	64.09	59.60	68.67	2.97	8.84
		25	1960 - 2017	54.36	54.31	49.92	58.78	2.90	8.40
		35	1960 - 2017	44.63	44.55	40.39	48.92	2.80	7.87
		45	1960 - 2017	35.12	35.07	31.11	39.21	2.67	7.14
		55	1960 - 2017	26.07	25.97	22.30	29.87	2.50	6.24
		65	1960 - 2017	17.64	17.56	14.26	21.13	2.25	5.05
		75	1960 - 2017	10.37	10.30	7.86	13.14	1.68	2.83
		85	1960 - 2017	5.22	5.19	3.95	6.54	0.82	0.67
	Male	All Ages	1960 - 2017	72.15	71.89	66.50	78.56	3.89	15.15
		1	1960 - 2017	72.04	71.43	68.01	77.84	3.31	10.95
		5	1960 - 2017	68.21	67.54	64.33	73.88	3.21	10.33
		15	1960 - 2017	58.40	57.78	54.66	63.94	3.11	9.69
		25	1960 - 2017	48.92	48.26	45.38	54.14	2.93	8.60
		35	1960 - 2017	39.43	38.78	36.04	44.42	2.79	7.80
		45	1960 - 2017	30.21	29.63	26.96	34.88	2.63	6.93
		55	1960 - 2017	21.68	21.14	18.63	25.85	2.42	5.83
		65	1960 - 2017	14.32	13.91	11.75	17.93	2.03	4.13
		75	1960 - 2017	8.48	8.11	6.93	11.01	1.35	1.81
		85	1960 - 2017	4.45	4.28	3.63	5.56	0.60	0.36

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Country Name	Sex	Age	Min Year	Max Year	Min	Max	Mean	Median	StdDev	Var
Poland	Both	All Ages	1960	2017	67.63	77.80	72.13	70.92	2.84	8.08
		0	1960	2017	67.63	77.80	72.13	70.92	2.84	8.08
		1	1960	2017	70.44	77.13	72.64	71.67	1.99	3.94
		5	1960	2017	66.82	73.17	68.82	67.94	1.90	3.62
		15	1960	2017	57.00	63.24	59.00	58.13	1.84	3.40
		25	1960	2017	47.46	53.50	49.42	48.58	1.77	3.14
		35	1960	2017	38.09	43.87	39.97	39.22	1.67	2.78
		45	1960	2017	29.25	34.51	30.90	30.19	1.55	2.40
		55	1960	2017	20.99	25.85	22.56	21.81	1.46	2.14
		65	1960	2017	13.59	18.25	15.23	14.59	1.39	1.93
		75	1960	2017	7.85	11.64	9.17	8.72	1.09	1.18
		85	1960	2017	4.15	6.20	4.89	4.65	0.54	0.30
	Male	All Ages	1960	2017	64.55	73.85	68.20	66.88	2.65	7.03
		0	1960	2017	64.55	73.85	68.20	66.88	2.65	7.03
		1	1960	2017	66.23	73.19	68.79	68.13	1.86	3.46
		5	1960	2017	62.39	69.24	64.99	64.45	1.80	3.22
		15	1960	2017	52.58	59.31	55.19	54.74	1.74	3.03
		25	1960	2017	43.23	49.66	45.77	45.41	1.66	2.76
		35	1960	2017	34.11	40.21	36.53	36.25	1.55	2.41
		45	1960	2017	25.64	31.06	27.74	27.45	1.40	1.95
		55	1960	2017	18.30	22.80	19.85	19.38	1.24	1.54
		65	1960	2017	11.77	15.86	13.21	12.67	1.14	1.30
		75	1960	2017	6.90	10.11	8.00	7.58	0.89	0.79
		85	1960	2017	3.82	5.60	4.42	4.22	0.46	0.21
	Female	All Ages	1960	2017	70.53	81.72	76.05	75.15	3.12	9.71
		0	1960	2017	70.53	81.72	76.05	75.15	3.12	9.71
		1	1960	2017	73.00	81.02	76.42	75.58	2.26	5.12
		5	1960	2017	69.43	77.06	72.60	71.75	2.17	4.69
		15	1960	2017	59.69	67.12	62.75	61.89	2.11	4.47
		25	1960	2017	50.05	57.25	52.97	52.09	2.06	4.24
		35	1960	2017	40.58	47.42	43.26	42.38	1.97	3.87
		45	1960	2017	31.33	37.76	33.82	33.00	1.86	3.45
		55	1960	2017	22.57	28.56	24.91	24.14	1.75	3.06
		65	1960	2017	14.59	20.13	16.75	16.14	1.62	2.62
Portugal	Both	All Ages	1950	2017	58.47	81.50	72.45	73.64	6.13	37.53
		0	1950	2017	58.47	81.50	72.45	73.64	6.13	37.53
		1	1950	2017	63.69	80.71	73.54	73.82	4.20	17.67
		5	1950	2017	62.98	76.76	70.21	70.10	3.51	12.33
		15	1950	2017	53.90	66.82	60.53	60.37	3.32	11.02
		25	1950	2017	45.17	56.99	51.05	50.94	3.15	9.93
		35	1950	2017	36.61	47.24	41.66	41.50	2.98	8.88
		45	1950	2017	28.00	37.68	32.52	32.28	2.80	7.82
		55	1950	2017	19.80	28.66	23.88	23.65	2.58	6.67
		65	1950	2017	12.59	20.23	16.00	15.86	2.22	4.92
		75	1950	2017	6.87	12.49	9.43	9.36	1.56	2.44
		85	1950	2017	3.62	6.36	4.98	4.93	0.74	0.54
	Male	All Ages	1950	2017	55.78	78.40	69.12	70.15	5.98	35.75
		0	1950	2017	55.78	78.40	69.12	70.15	5.98	35.75
		1	1950	2017	61.14	77.63	70.29	70.39	4.03	16.21
		5	1950	2017	60.37	73.69	66.96	66.68	3.38	11.43
		15	1950	2017	51.29	63.76	57.31	56.99	3.18	10.10
		25	1950	2017	42.63	53.98	48.01	47.80	2.97	8.84
		35	1950	2017	34.22	44.30	38.82	38.57	2.79	7.78
		45	1950	2017	25.88	34.85	29.91	29.56	2.59	6.73
		55	1950	2017	18.04	26.12	21.62	21.31	2.37	5.62
		65	1950	2017	11.36	18.25	14.28	14.08	1.99	3.98
		75	1950	2017	6.13	11.10	8.34	8.28	1.36	1.85
		85	1950	2017	3.16	5.60	4.41	4.37	0.64	0.40
	Female	All Ages	1950	2017	61.02	84.38	75.70	77.07	6.29	39.51
		0	1950	2017	61.02	84.38	75.70	77.07	6.29	39.51
		1	1950	2017	66.03	83.57	76.67	77.16	4.42	19.55
		5	1950	2017	65.36	79.61	73.33	73.44	3.69	13.59
		15	1950	2017	56.27	69.67	63.61	63.65	3.51	12.32
		25	1950	2017	47.44	59.79	53.92	53.95	3.37	11.34
		35	1950	2017	38.71	49.94	44.32	44.28	3.20	10.23
		45	1950	2017	29.85	40.27	34.92	34.82	3.02	9.14
		55	1950	2017	21.26	30.92	25.88	25.75	2.81	7.91
		65	1950	2017	13.52	21.89	17.40	17.33	2.45	5.99
		75	1950	2017	7.36	13.51	10.18	10.07	1.74	3.03
		85	1950	2017	3.83	6.80	5.25	5.18	0.81	0.66

Continue on next page.

Country Name	Sex	Age	Min Year	Max Year	Min	Max	Mean	Median	StdDev	Var
Sweden	Both	All Ages	1860	2017	41.01	82.44	71.42	74.15	9.59	91.93
		0	1860	2017	41.01	82.44	71.42	74.15	9.59	91.93
		1	1860	2017	47.13	81.63	72.16	74.09	7.70	59.33
		5	1860	2017	50.51	77.67	68.96	70.25	6.44	41.52
		15	1860	2017	42.87	67.72	59.56	60.46	5.66	32.07
		25	1860	2017	37.54	57.93	50.38	50.88	4.91	24.07
		35	1860	2017	30.19	48.22	41.23	41.28	4.18	17.47
		45	1860	2017	23.07	38.55	32.19	31.96	3.55	12.61
		55	1860	2017	16.37	29.14	23.57	23.12	2.98	8.89
		65	1860	2017	10.36	20.36	15.75	15.17	2.40	5.74
		75	1860	2017	5.86	12.54	9.28	8.81	1.68	2.81
		85	1860	2017	3.15	6.38	4.79	4.57	0.85	0.72
	Male	All Ages	1860	2017	39.32	80.73	69.41	71.85	9.23	85.15
		0	1860	2017	39.32	80.73	69.41	71.85	9.23	85.15
		1	1860	2017	45.71	79.92	70.31	71.90	7.22	52.18
		5	1860	2017	49.07	75.95	67.12	68.07	5.95	35.39
		15	1860	2017	41.28	66.01	57.73	58.31	5.19	26.89
		25	1860	2017	36.09	56.29	48.65	48.85	4.44	19.74
		35	1860	2017	28.75	46.69	39.59	39.41	3.75	14.07
		45	1860	2017	21.64	37.10	30.62	30.17	3.15	9.89
		55	1860	2017	15.16	27.77	22.14	21.54	2.56	6.55
		65	1860	2017	9.69	19.14	14.60	13.99	1.96	3.85
		75	1860	2017	5.47	11.54	8.51	8.12	1.30	1.68
		85	1860	2017	2.75	5.74	4.37	4.31	0.63	0.39
	Female	All Ages	1860	2017	42.72	84.12	73.44	76.63	9.98	99.65
		0	1860	2017	42.72	84.12	73.44	76.63	9.98	99.65
		1	1860	2017	48.52	83.31	74.02	76.41	8.24	67.97
		5	1860	2017	51.93	79.35	70.79	72.54	7.01	49.17
		15	1860	2017	44.45	69.40	61.38	62.71	6.22	38.69
		25	1860	2017	38.89	59.52	52.08	52.93	5.46	29.77
		35	1860	2017	31.50	49.69	42.84	43.27	4.70	22.06
		45	1860	2017	24.27	39.92	33.71	33.79	4.04	16.34
		55	1860	2017	17.09	30.43	24.92	24.73	3.47	12.07
		65	1860	2017	10.82	21.48	16.79	16.39	2.86	8.18
		75	1860	2017	6.13	13.41	9.90	9.41	2.00	4.02
		85	1860	2017	3.35	6.81	5.05	4.81	0.98	0.96
Switzerland	Both	All Ages	1895	2017	46.30	83.46	72.88	74.79	8.28	68.60
		0	1895	2017	46.30	83.46	72.88	74.79	8.28	68.60
		1	1895	2017	49.79	82.75	73.41	74.59	6.72	45.10
		5	1895	2017	47.95	78.78	69.85	70.79	6.18	38.18
		15	1895	2017	39.59	68.83	60.20	61.01	5.84	34.07
		25	1895	2017	33.73	58.98	50.84	51.54	5.38	28.99
		35	1895	2017	29.47	49.18	41.51	41.95	4.90	24.05
		45	1895	2017	22.60	39.46	32.32	32.57	4.43	19.61
		55	1895	2017	15.64	30.06	23.66	23.76	3.87	15.00
		65	1895	2017	9.82	21.26	15.90	15.86	3.16	9.97
		75	1895	2017	5.59	13.31	9.46	9.36	2.17	4.72
		85	1895	2017	3.04	6.76	4.88	4.77	1.04	1.09
	Male	All Ages	1895	2017	43.76	81.53	70.21	71.50	7.94	63.10
		0	1895	2017	43.76	81.53	70.21	71.50	7.94	63.10
		1	1895	2017	47.49	80.80	70.87	71.38	6.27	39.32
		5	1895	2017	45.49	76.83	67.33	67.60	5.74	32.98
		15	1895	2017	36.95	66.88	57.70	57.85	5.41	29.29
		25	1895	2017	31.35	57.07	48.48	48.60	4.99	24.91
		35	1895	2017	27.90	47.31	39.25	39.13	4.55	20.68
		45	1895	2017	21.77	37.64	30.17	29.84	4.07	16.57
		55	1895	2017	15.32	28.34	21.73	21.29	3.46	11.98
		65	1895	2017	9.80	19.75	14.38	13.89	2.70	7.28
		75	1895	2017	5.51	12.14	8.49	8.17	1.77	3.14
		85	1895	2017	2.97	6.02	4.41	4.37	0.83	0.68
	Female	All Ages	1895	2017	48.41	85.37	75.45	78.01	8.60	73.94
		0	1895	2017	48.41	85.37	75.45	78.01	8.60	73.94
		1	1895	2017	52.12	84.63	75.84	77.71	7.17	51.35
		5	1895	2017	50.45	80.67	72.25	73.87	6.63	43.95
		15	1895	2017	42.29	70.72	62.57	64.07	6.28	39.41
		25	1895	2017	36.15	60.80	53.06	54.35	5.78	33.43
		35	1895	2017	30.85	50.93	43.61	44.62	5.26	27.62
		45	1895	2017	23.29	41.15	34.29	35.10	4.78	22.85
		55	1895	2017	15.91	31.60	25.37	25.98	4.28	18.28
		65	1895	2017	9.76	22.54	17.15	17.46	3.57	12.74
		75	1895	2017	5.53	14.18	10.14	10.15	2.46	6.06
		85	1895	2017	3.09	7.18	5.13	5.03	1.14	1.31

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Country Name	Sex	Age	Min Year	Max Year	Min	Max	Mean	Median	StdDev	Var
United States	Both	All Ages	1935	2017	60.35	79.05	73.48	74.56	4.19	17.53
		0	1935	2017	60.35	79.05	73.48	74.56	4.19	17.53
		1	1935	2017	63.19	78.51	73.66	74.39	3.44	11.82
		5	1935	2017	60.32	74.59	69.87	70.56	3.28	10.78
		15	1935	2017	51.14	64.67	60.09	60.73	3.16	9.98
		25	1935	2017	42.45	55.06	50.66	51.25	3.03	9.17
		35	1935	2017	34.01	45.60	41.31	41.82	2.91	8.45
		45	1935	2017	25.98	36.37	32.23	32.61	2.71	7.35
		55	1935	2017	18.67	27.64	23.85	24.12	2.38	5.68
		65	1935	2017	12.28	19.72	16.47	16.72	1.92	3.70
		75	1935	2017	7.36	12.63	10.32	10.58	1.34	1.81
		85	1935	2017	4.16	7.00	5.72	5.98	0.69	0.48
	Male	All Ages	1935	2017	58.35	76.61	70.35	70.97	4.26	18.16
		0	1935	2017	58.35	76.61	70.35	70.97	4.26	18.16
		1	1935	2017	61.50	76.10	70.62	70.84	3.49	12.15
		5	1935	2017	58.68	72.18	66.84	67.02	3.34	11.14
		15	1935	2017	49.58	62.28	57.09	57.22	3.21	10.29
		25	1935	2017	40.97	52.80	47.87	47.93	3.06	9.39
		35	1935	2017	32.57	43.52	38.68	38.68	2.97	8.84
		45	1935	2017	24.71	34.42	29.78	29.61	2.79	7.81
		55	1935	2017	17.68	25.89	21.66	21.36	2.44	5.97
		65	1935	2017	11.63	18.34	14.73	14.42	1.90	3.62
		75	1935	2017	6.95	11.64	9.13	8.95	1.22	1.48
		85	1935	2017	3.93	6.40	5.05	5.11	0.55	0.31
	Female	All Ages	1935	2017	62.60	81.42	76.64	78.09	4.04	16.34
		0	1935	2017	62.60	81.42	76.64	78.09	4.04	16.34
		1	1935	2017	65.09	80.86	76.72	77.88	3.35	11.24
		5	1935	2017	62.17	76.93	72.92	74.04	3.19	10.20
		15	1935	2017	52.91	67.00	63.11	64.19	3.08	9.50
		25	1935	2017	44.14	57.22	53.46	54.49	2.94	8.67
		35	1935	2017	35.64	47.61	43.91	44.84	2.78	7.72
		45	1935	2017	27.42	38.21	34.64	35.40	2.56	6.56
		55	1935	2017	19.77	29.24	25.92	26.54	2.28	5.19
		65	1935	2017	12.98	20.92	17.99	18.58	1.93	3.71
		75	1935	2017	7.76	13.40	11.20	11.72	1.42	2.03
		85	1935	2017	4.34	7.36	6.09	6.38	0.74	0.55
W.E. Germany	Both	All Ages	1960	2017	69.24	80.94	75.27	75.32	3.72	13.85
		0	1960	2017	69.24	80.94	75.24	75.26	3.73	13.90
		1	1960	2017	70.76	80.21	75.09	74.82	3.16	10.00
		5	1960	2017	67.14	76.25	71.25	70.91	3.07	9.41
		15	1960	2017	57.42	66.31	61.42	61.15	2.98	8.88
		25	1960	2017	47.96	56.47	51.81	51.51	2.85	8.10
		35	1960	2017	38.56	46.69	42.22	41.91	2.72	7.43
		45	1960	2017	29.37	37.07	32.87	32.61	2.58	6.65
		55	1960	2017	20.79	27.94	24.11	23.88	2.40	5.75
		65	1960	2017	13.38	19.65	16.24	16.14	2.11	4.46
		75	1960	2017	7.50	12.22	9.67	9.54	1.54	2.37
		85	1960	2017	3.82	6.22	4.99	4.93	0.77	0.59
	Male	All Ages	1960	2017	66.50	78.56	72.15	71.89	3.89	15.15
		0	1960	2017	66.50	78.56	72.13	71.83	3.90	15.19
		1	1960	2017	68.01	77.84	72.04	71.43	3.31	10.95
		5	1960	2017	64.33	73.88	68.21	67.54	3.21	10.33
		15	1960	2017	54.66	63.94	58.40	57.78	3.11	9.69
		25	1960	2017	45.38	54.14	48.92	48.26	2.93	8.60
		35	1960	2017	36.04	44.42	39.43	38.78	2.79	7.80
		45	1960	2017	26.96	34.88	30.21	29.63	2.63	6.93
		55	1960	2017	18.63	25.85	21.68	21.14	2.42	5.83
		65	1960	2017	11.75	17.93	14.32	13.91	2.03	4.13
		75	1960	2017	6.93	11.01	8.48	8.11	1.35	1.81
		85	1960	2017	3.63	5.56	4.45	4.28	0.60	0.36
	Female	All Ages	1960	2017	71.75	83.33	78.09	78.37	3.65	13.29
		0	1960	2017	71.75	83.33	78.07	78.29	3.65	13.33
		1	1960	2017	73.03	82.58	77.83	77.77	3.13	9.81
		5	1960	2017	69.37	78.63	73.98	73.84	3.04	9.26
		15	1960	2017	59.60	68.67	64.13	64.09	2.97	8.84
		25	1960	2017	49.92	58.78	54.36	54.31	2.90	8.40
		35	1960	2017	40.39	48.92	44.63	44.55	2.80	7.87
		45	1960	2017	31.11	39.21	35.12	35.07	2.67	7.14
		55	1960	2017	22.30	29.87	26.07	25.97	2.50	6.24
		65	1960	2017	14.26	21.13	17.64	17.56	2.25	5.05
		75	1960	2017	7.86	13.14	10.37	10.30	1.68	2.83
		85	1960	2017	3.95	6.54	5.22	5.19	0.82	0.67

Summary statistics for life expectancy at birth (LEB) for the all combinations of sexes (male, female, and both), selected ages (All Ages, 0, 1, 5, 15, ..., 85), and country. The column “Period” indicates the years covered for each country in the dataset.

Table 1.7: Country Weights Derived from Synthetic Control Models

Model	Age	Sex	England and Wales	Denmark	Norway	France	Netherlands	Sweden
Century. 1900	All Ages	Both	97.1%	0.0%	2.8%	0.0%	0.0%	0.0%
		Female	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	94.2%	0.0%	5.7%	0.0%	0.1%	0.0%
	1	Both	99.9%	0.0%	0.0%	0.1%	0.0%	0.0%
		Female	99.9%	0.0%	0.0%	0.1%	0.0%	0.0%
		Male	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	87.6%	0.0%	0.0%	12.4%	0.0%	0.0%
		Female	90.5%	0.0%	0.0%	9.5%	0.0%	0.0%
		Male	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15	Both	94.5%	0.0%	0.0%	5.5%	0.0%	0.0%
		Female	86.7%	0.0%	0.0%	13.3%	0.0%	0.0%
		Male	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	98.0%	0.0%	2.0%	0.0%	0.0%	0.0%
		Female	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	97.7%	0.0%	2.3%	0.0%	0.0%	0.0%
	35	Both	90.8%	0.0%	9.2%	0.0%	0.0%	0.0%
		Female	87.8%	12.1%	0.1%	0.0%	0.0%	0.0%
		Male	92.2%	0.3%	7.4%	0.0%	0.0%	0.0%
	45	Both	88.9%	0.0%	11.1%	0.0%	0.0%	0.0%
		Female	80.5%	19.5%	0.0%	0.0%	0.0%	0.0%
		Male	86.2%	13.7%	0.1%	0.0%	0.0%	0.0%
	55	Both	84.6%	0.0%	15.4%	0.0%	0.0%	0.0%
		Female	69.2%	30.7%	0.0%	0.0%	0.0%	0.0%
		Male	89.6%	1.9%	8.5%	0.0%	0.0%	0.0%
	65	Both	57.1%	36.8%	6.1%	0.0%	0.0%	0.0%
		Female	52.8%	42.1%	5.1%	0.0%	0.0%	0.0%
		Male	72.6%	18.8%	8.6%	0.0%	0.0%	0.0%
	75	Both	28.5%	71.4%	0.1%	0.0%	0.0%	0.0%
		Female	26.2%	73.7%	0.0%	0.0%	0.0%	0.0%
		Male	62.7%	28.5%	8.9%	0.0%	0.0%	0.0%
	85	Both	84.9%	0.0%	15.1%	0.0%	0.0%	0.0%
		Female	91.0%	0.0%	9.0%	0.0%	0.0%	0.0%
		Male	88.8%	0.0%	11.1%	0.0%	0.1%	0.0%

Model	Age	Sex	England and Wales	Switzerland	Denmark	Netherlands	France	Norway	Sweden	Italy	Finland
Post.WWI. 1919	All Ages	Both	51.7%	44.8%	0.3%	0.1%	0.0%	3.1%	0.0%	0.0%	0.0%
		Female	89.8%	0.0%	0.0%	0.0%	10.2%	0.0%	0.0%	0.0%	0.0%
		Male	26.8%	73.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1	Both	35.0%	64.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	89.3%	0.0%	0.0%	0.0%	10.6%	0.0%	0.0%	0.0%	0.0%
		Male	47.3%	0.1%	0.0%	52.6%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	6.2%	86.8%	5.7%	0.9%	0.0%	0.2%	0.2%	0.0%	0.0%
		Female	50.5%	46.2%	0.0%	0.0%	0.0%	3.2%	0.0%	0.0%	0.0%
		Male	35.1%	0.0%	62.0%	0.0%	0.0%	2.9%	0.0%	0.0%	0.0%
	15	Both	15.5%	72.1%	12.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	29.9%	70.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	4.9%	75.6%	19.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	85.8%	0.0%	14.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	32.4%	67.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	5.4%	77.8%	16.6%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
	35	Both	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	37.8%	62.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	43.7%	49.8%	6.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	45	Both	51.2%	46.6%	1.0%	0.0%	0.0%	0.9%	0.3%	0.0%	0.0%
		Female	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	98.5%	0.0%	0.0%	0.0%	1.5%	0.0%	0.0%	0.0%	0.0%
	55	Both	91.3%	0.0%	0.0%	0.0%	8.7%	0.0%	0.0%	0.0%	0.0%
		Female	90.0%	0.0%	0.0%	0.0%	10.0%	0.0%	0.0%	0.0%	0.0%
		Male	98.3%	0.0%	0.0%	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%
	65	Both	88.5%	6.9%	0.0%	0.0%	4.6%	0.0%	0.0%	0.0%	0.0%
		Female	86.9%	0.0%	2.7%	10.4%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	89.9%	0.0%	0.0%	0.0%	9.9%	0.2%	0.0%	0.0%	0.0%
	75	Both	89.1%	0.0%	3.6%	0.0%	0.0%	7.3%	0.0%	0.0%	0.0%
		Female	59.5%	0.0%	27.9%	12.6%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	94.9%	0.0%	0.0%	0.0%	0.0%	5.1%	0.0%	0.0%	0.0%
	85	Both	80.9%	0.0%	13.4%	5.7%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	83.6%	0.0%	0.0%	4.8%	0.0%	11.6%	0.0%	0.0%	0.0%
		Male	38.3%	0.0%	15.9%	45.8%	0.0%	0.0%	0.0%	0.0%	0.0%

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Model	Age	Sex	England and Wales	Northern Ireland	Denmark	Switzerland	Spain	Netherlands	Finland	France	Italy	Norway	Sweden	Canada
Post.WWII. 1946	All Ages	Both	20.3%	77.4%	0.0%	1.0%	0.0%	0.0%	0.5%	0.7%	0.0%	0.1%	0.0%	0.0%
		Female	27.1%	63.5%	7.5%	0.0%	0.0%	1.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	20.5%	79.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1	Both	0.3%	65.5%	16.2%	0.5%	0.1%	0.1%	0.1%	16.9%	0.1%	0.1%	0.2%	0.0%
		Female	47.2%	52.7%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	55.7%	44.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	49.1%	32.0%	0.0%	0.0%	0.0%	0.0%	0.0%	18.7%	0.0%	0.0%	0.0%	0.0%
		Female	5.2%	53.3%	17.5%	6.3%	0.0%	17.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	64.0%	36.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15	Both	54.4%	32.1%	0.0%	0.0%	13.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	26.4%	51.4%	0.0%	0.0%	0.0%	22.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	90.7%	0.5%	0.0%	0.0%	8.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	49.9%	36.2%	0.0%	0.0%	13.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	34.0%	50.0%	0.0%	0.0%	0.0%	16.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	77.7%	22.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	35	Both	28.2%	68.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.6%	0.0%	0.0%	0.0%
		Female	30.2%	48.9%	20.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	26.3%	73.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	45	Both	37.7%	38.3%	0.0%	0.0%	0.0%	0.0%	23.8%	0.2%	0.0%	0.0%	0.0%	0.0%
		Female	30.7%	51.1%	9.1%	0.0%	0.0%	9.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	49.9%	0.0%	0.0%	50.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	55	Both	17.2%	72.7%	0.0%	0.0%	0.0%	0.0%	9.7%	0.3%	0.0%	0.1%	0.0%	0.0%
		Female	28.2%	54.7%	14.6%	0.0%	0.0%	2.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	77.1%	0.7%	0.0%	0.0%	22.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	65	Both	8.0%	59.4%	0.0%	17.1%	1.0%	0.0%	14.2%	0.2%	0.0%	0.2%	0.0%	0.0%
		Female	19.4%	57.3%	23.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	72.5%	0.0%	0.0%	0.0%	27.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	75	Both	37.5%	0.0%	3.5%	51.1%	0.0%	0.0%	7.8%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	27.6%	0.0%	40.9%	31.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	80.8%	0.0%	0.0%	0.0%	19.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	85	Both	35.7%	4.6%	29.7%	23.4%	0.0%	0.0%	6.6%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	47.5%	0.0%	34.3%	0.0%	0.0%	18.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	66.5%	0.0%	0.0%	20.6%	0.0%	12.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Model	Age	Sex	Northern Ireland	England and Wales	Switzerland	Finland	Denmark	Spain	France	United States	Norway	Sweden	Netherlands	Italy	Canada
Post.WWII. 1955	All Ages	Both	69.0%	17.3%	0.2%	11.1%	2.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	69.1%	7.7%	23.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
		Male	81.3%	18.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1	Both	74.8%	13.2%	0.8%	0.1%	0.4%	0.0%	10.5%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%
		Female	69.7%	11.1%	0.0%	0.0%	19.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	42.2%	57.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	70.9%	15.5%	0.1%	0.1%	0.1%	3.6%	9.5%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%
		Female	66.1%	21.4%	12.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	36.1%	63.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15	Both	87.2%	9.5%	0.0%	0.0%	0.0%	3.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	64.3%	11.0%	24.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	35.0%	65.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	84.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	15.5%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	60.0%	20.1%	19.8%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	31.6%	68.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	35	Both	38.5%	34.3%	0.0%	27.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	57.8%	18.0%	24.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	88.9%	0.0%	0.0%	0.0%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	45	Both	21.1%	35.3%	0.0%	43.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	60.2%	19.7%	20.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	77.2%	0.0%	0.0%	0.0%	22.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	55	Both	23.5%	31.4%	0.0%	45.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	61.5%	16.9%	21.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	88.7%	0.0%	0.0%	0.0%	11.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	65	Both	71.0%	0.0%	0.0%	29.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	76.4%	14.6%	0.0%	0.0%	9.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	80.9%	0.0%	0.0%	0.0%	19.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	75	Both	48.3%	6.7%	21.0%	23.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	49.7%	0.0%	0.0%	0.0%	50.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	80.0%	0.0%	0.0%	0.0%	20.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	85	Both	0.0%	30.5%	34.4%	19.6%	15.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	34.3%	28.5%	0.0%	37.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	3.5%	55.5%	41.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

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Model	Age	Sex	Northern Ireland	Ireland	England and Wales	Finland	Denmark	Austria	Spain	Netherlands	Switzerland	France	Sweden	Norway	Italy	United States	Portugal	Canada
Modern. 1970	All Ages	Both	47.6%	0.0%	0.2%	24.2%	1.9%	25.7%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	57.1%	39.2%	3.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1	Both	40.2%	57.8%	1.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.0%	0.3%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%
		Female	38.0%	58.7%	3.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	0.0%	79.6%	0.0%	0.0%	0.0%	20.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	48.5%	49.5%	0.6%	0.1%	0.3%	0.1%	0.0%	0.2%	0.1%	0.4%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
		Female	32.8%	64.5%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.2%	0.0%	83.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15	Both	96.5%	2.9%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	22.0%	72.5%	5.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.3%	0.0%	83.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	98.9%	1.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	89.6%	10.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.3%	0.0%	83.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	35	Both	87.2%	11.9%	0.2%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
		Female	9.4%	88.0%	2.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	45	Both	88.9%	0.0%	0.2%	10.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.2%	93.4%	6.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	22.3%	77.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	55	Both	64.9%	0.0%	0.3%	34.1%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	93.4%	6.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.3%	0.0%	83.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	65	Both	46.8%	0.0%	0.4%	52.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	94.9%	5.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.5%	0.0%	83.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	75	Both	50.5%	0.0%	9.1%	40.2%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	94.9%	5.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	16.1%	0.0%	83.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	85	Both	31.3%	0.0%	26.3%	32.1%	0.0%	0.0%	0.0%	0.0%	10.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	0.0%	37.2%	2.1%	0.0%	47.8%	0.0%	0.0%	12.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	0.0%	21.6%	78.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Model	Age	Sex	Ireland	Luxembourg	Northern Ireland	England and Wales	Finland	Portugal	Austria	Denmark	Netherlands	W.E. Germany	Spain	Sweden	Norway	France	Poland	Italy	United States	Switzerland	Canada
Modern. 1980	All Ages	Both	0.0%	0.0%	42.8%	16.6%	0.0%	15.9%	24.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	84.6%	0.0%	15.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	28.6%	62.4%	0.2%	8.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1	Both	23.4%	60.1%	5.1%	11.2%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.6%	61.6%	0.0%	8.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5	Both	57.4%	0.1%	41.6%	0.2%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
		Female	99.0%	0.0%	0.0%	1.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.4%	61.4%	0.0%	9.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	15	Both	31.4%	45.9%	0.2%	21.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.3%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%
		Female	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.4%	61.4%	0.0%	9.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	25	Both	0.0%	0.0%	79.6%	0.0%	0.0%	20.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	95.2%	0.0%	0.1%	4.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.4%	62.3%	0.0%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	35	Both	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	96.4%	0.0%	0.2%	3.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.3%	59.2%	0.0%	11.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	45	Both	0.0%	65.9%	27.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	97.2%	0.0%	0.0%	2.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.6%	61.8%	0.0%	8.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	55	Both	0.0%	69.4%	23.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	89.8%	0.0%	9.2%	1.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.9%	61.7%	0.0%	8.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	65	Both	0.0%	27.1%	47.8%	0.0%	20.7%	0.0%	0.0%	0.0%	0.0%	4.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	60.4%	23.0%	0.0%	16.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	29.6%	62.0%	0.0%	8.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	75	Both	0.0%	11.2%	42.8%	22.9%	23.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	72.9%	0.0%	0.3%	5.0%	0.0%	0.0%	0.0%	21.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	28.6%	34.1%	0.0%	37.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	85	Both	0.0%	0.5%	19.8%	43.7%	21.5%	0.0%	10.9%	3.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Female	36.3%	16.0%	0.0%	29.1%	0.0%	0.0%	0.0%	0.0%	18.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Male	63.0%	6.2%	0.0%	30.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Note:

This table displays the country weights assigned by each synthetic control model, broken down by breakpoint year, age group, and sex. Each column represents a potential donor country; darker blue shading indicates higher weights, while lighter blue indicates smaller contributions, and blank cells reflect zero weight. Most models are dominated by one or a few countries, illustrating that a small set of donors typically drives the counterfactual fit.

Table 1.8: Covariate Weights Derived from SCM by Model

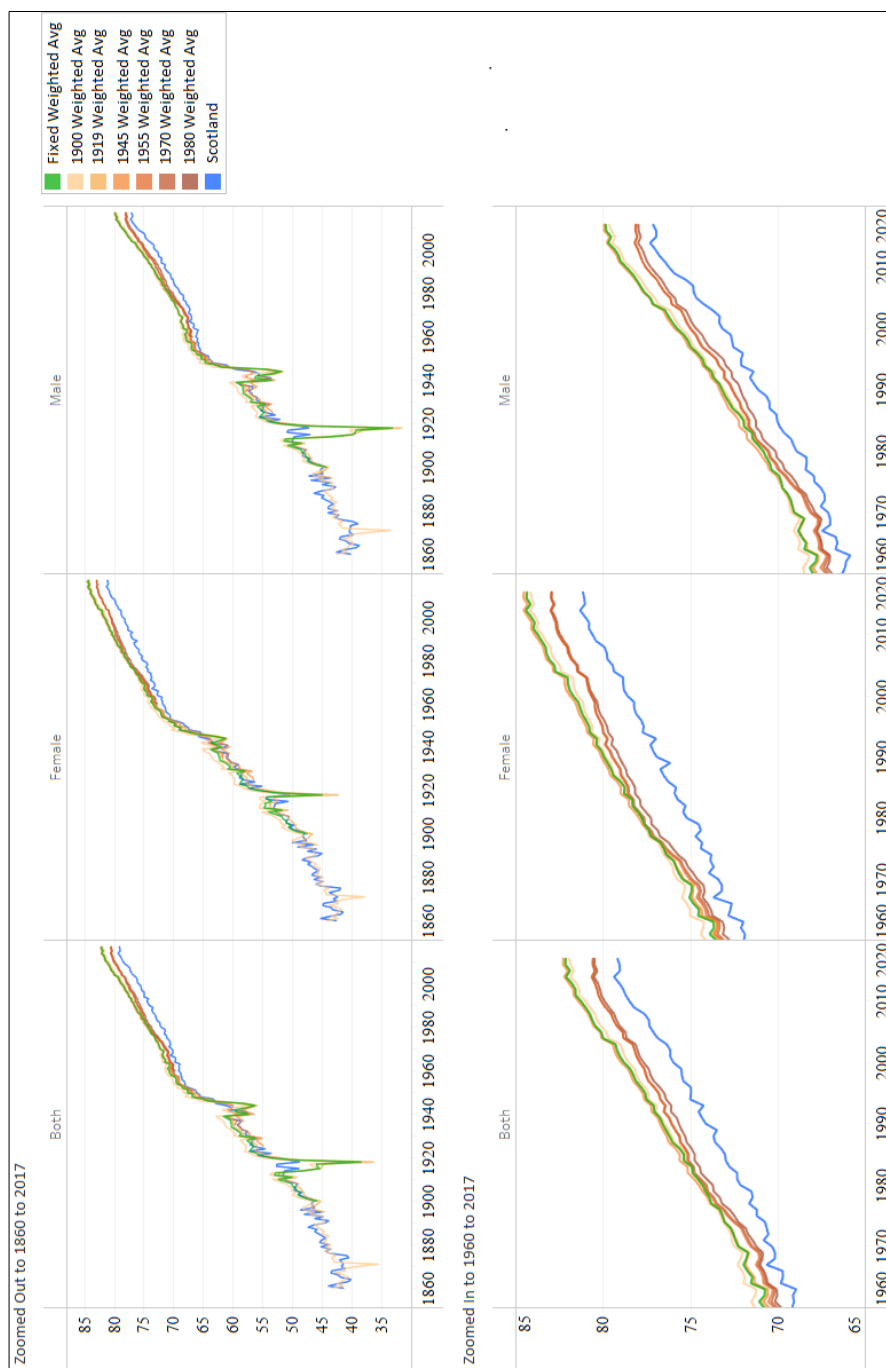
Metric	Age	Sex	Century.1900							Post.WWI.1919							Post.WWII.1946						
			GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density		GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density		GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density	
Life Expectancy	All Ages	Both	19.7%	0.0%	41.2%	9.7%	9.4%	20.0%		47.6%	0.3%	4.8%	8.3%	9.1%	29.9%		0.0%	31.7%	23.0%	25.1%	16.7%	3.4%	
		Female	1.5%	13.9%	80.6%		3.9%	0.1%		92.5%	0.0%	5.8%		0.2%	1.5%		3.1%	11.1%	73.9%		10.6%	1.3%	
		Male	33.0%	3.5%	28.5%		2.0%	33.0%		61.9%	0.7%	6.4%		27.6%	3.3%		0.8%	13.4%	58.9%		1.2%	25.8%	
Life Expectancy at Age	1	Both	28.1%	0.0%	49.4%	0.1%	0.6%	21.9%		54.3%	0.2%	0.1%	0.2%	4.7%	40.5%		0.5%	13.0%	44.7%	7.1%	32.1%	2.6%	
		Female	32.9%	0.0%	58.5%		0.0%	8.6%		98.5%	0.0%	1.5%		0.0%	0.0%		2.4%	14.2%	60.7%		2.6%	20.2%	
		Male	18.1%	6.5%	74.1%		1.1%	0.2%		44.9%	6.7%	21.7%		22.2%	4.4%		2.2%	12.1%	69.5%		0.5%	15.6%	
	5	Both	60.7%	1.7%	31.4%	0.5%	0.0%	5.7%		20.0%	1.5%	0.0%	3.4%	73.5%	1.6%		0.3%	1.6%	39.0%	2.4%	0.1%	56.6%	
		Female	49.6%	2.2%	32.5%		0.0%	15.7%		43.8%	1.2%	0.0%		2.5%	52.5%		0.2%	0.4%	3.5%		91.7%	4.3%	
		Male	26.4%	1.1%	47.8%		0.5%	24.2%		4.6%	5.8%	2.1%		4.9%	82.6%		4.8%	6.7%	85.5%		3.0%	0.0%	
	15	Both	46.4%	2.0%	43.5%	0.1%	1.1%	7.0%		49.7%	5.9%	0.2%	4.4%	36.0%	3.9%		1.4%	0.0%	79.9%	0.9%	0.8%	16.9%	
		Female	47.7%	0.0%	25.7%		0.1%	26.5%		67.2%	0.0%	8.6%		24.0%	0.2%		4.1%	4.1%	77.2%		14.0%	0.6%	
		Male	24.6%	1.1%	45.6%		0.2%	28.6%		1.0%	0.2%	0.0%		96.2%	2.6%		38.6%	0.3%	33.7%		0.1%	27.4%	
	25	Both	18.5%	10.2%	39.7%	18.5%	1.8%	11.3%		36.2%	32.0%	30.9%	0.0%	0.7%	0.2%		15.8%	10.9%	19.3%	50.4%	1.0%	2.6%	
		Female	29.7%	2.7%	47.9%		0.5%	19.3%		90.9%	0.0%	0.0%		8.6%	0.6%		4.3%	3.2%	83.6%		8.2%	0.7%	
		Male	35.7%	4.5%	39.8%		1.4%	18.6%		8.7%	1.3%	0.0%		63.2%	26.8%		13.7%	8.5%	74.6%		2.5%	0.6%	
	35	Both	27.4%	2.5%	25.4%	9.7%	6.1%	28.8%		0.0%	0.1%	88.1%	11.6%	0.0%	0.2%		3.0%	0.0%	20.3%	63.8%	0.0%	12.8%	
		Female	28.7%	12.9%	32.7%		1.4%	24.3%		84.9%	0.0%	3.7%		11.1%	0.2%		3.4%	15.8%	50.0%		6.2%	24.7%	
		Male	0.7%	2.1%	5.2%		0.0%	91.9%		75.6%	4.5%	3.5%		12.7%	3.7%		0.8%	15.1%	41.0%		0.1%	43.1%	
	45	Both	9.7%	2.6%	29.3%	17.5%	21.0%	20.0%		53.1%	0.0%	0.0%	43.4%	3.5%	0.0%		2.7%	13.8%	2.3%	45.3%	10.1%	25.8%	
		Female	28.4%	18.8%	31.5%		0.5%	20.7%		17.7%	24.8%	55.6%		1.3%	0.7%		3.2%	10.8%	56.0%		6.2%	23.8%	
		Male	34.1%	13.2%	30.3%		0.3%	22.2%		52.6%	2.8%	43.6%		0.1%	1.0%		69.3%	0.0%	4.2%		0.7%	25.8%	
	55	Both	9.9%	0.1%	31.6%	19.7%	38.3%	0.3%		83.0%	0.0%	14.8%	1.8%	0.0%	0.4%		0.1%	22.6%	24.0%	31.5%	0.1%	21.6%	
		Female	18.9%	15.9%	18.9%		5.2%	41.0%		92.4%	0.1%	6.6%		0.2%	0.7%		2.9%	12.4%	53.3%		6.8%	24.5%	
		Male	0.7%	1.7%	4.2%		0.3%	93.0%		50.4%	0.9%	44.3%		0.1%	4.2%		4.7%	0.2%	80.3%		0.5%	14.2%	
	65	Both	0.8%	1.6%	1.8%	1.1%	2.8%	92.0%		18.4%	3.8%	35.2%	21.1%	21.1%	0.3%		0.1%	0.7%	5.4%	47.8%	12.8%	33.1%	
		Female	0.1%	0.8%	0.9%		0.8%	97.4%		37.6%	21.3%	29.7%		2.7%	8.8%		1.9%	45.8%	44.4%		0.0%	7.8%	
		Male	2.0%	0.2%	0.0%		0.0%	97.7%		91.5%	0.0%	6.0%		0.1%	2.3%		1.6%	0.2%	56.0%		0.1%	42.1%	
	75	Both	0.0%	36.6%	15.1%	4.6%	4.8%	38.9%		21.1%	6.6%	19.1%	10.7%	16.1%	26.3%		8.3%	2.3%	1.1%	70.5%	2.1%	15.7%	
		Female	7.3%	20.6%	3.7%		15.6%	52.9%		22.9%	23.3%	17.5%		16.0%	20.3%		31.3%	4.7%	23.6%		14.6%	25.9%	
		Male	0.1%	0.2%	0.2%		0.2%	99.3%		30.1%	18.0%	30.2%		0.2%	21.5%		5.1%	0.1%	62.0%		0.4%	32.3%	
	85	Both	94.3%	0.4%	3.6%	0.6%	0.9%	0.2%		23.3%	17.5%	28.1%	7.1%	13.9%	10.0%		13.4%	19.8%	17.0%	11.0%	19.5%	19.2%	
		Female	1.0%	0.1%	0.8%		0.0%	98.1%		22.3%	1.6%	2.6%		3.0%	70.4%		34.2%	10.5%	45.6%		9.3%	0.3%	
		Male	1.7%	0.0%	0.8%		0.3%	97.2%		22.2%	18.3%	13.4%		39.8%	6.3%		62.4%	0.3%	6.1%		0.9%	30.3%	

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Metric	Age	Sex	Post.WWII.1955						Modern.1970						Modern.1980					
			GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density	GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density	GDP Per Capita	Latitudinal Distance	Longitudinal Distance	Male Percentage	Population	Population Density
Life Expectancy	All Ages	Both	1.5%	16.4%	13.0%	3.3%	54.3%	11.4%	0.3%	25.6%	0.0%	29.9%	12.7%	31.5%	1.3%	0.9%	24.5%	21.7%	26.5%	25.1%
		Female	0.1%	0.0%	3.0%		94.9%	1.9%	0.3%	1.9%	84.8%		13.0%	0.0%	0.6%	4.1%	87.8%		4.9%	2.6%
		Male	0.7%	7.9%	66.4%		6.3%	18.7%	0.0%	12.8%	70.2%		0.5%	16.5%	38.4%	0.0%	1.0%		60.3%	0.3%
Life Expectancy at Age	1	Both	1.0%	0.8%	62.4%	1.9%	30.5%	3.5%	0.0%	3.9%	57.5%	1.5%	36.3%	0.7%	27.3%	0.4%	11.7%	0.8%	59.5%	0.3%
		Female	1.3%	32.4%	47.5%		0.7%	18.0%	0.3%	2.3%	78.3%		16.9%	2.2%	0.5%	2.9%	82.8%		11.1%	2.7%
		Male	3.7%	3.1%	73.3%		14.3%	5.7%	28.1%	0.0%	47.1%		0.3%	24.5%	14.2%	0.0%	0.8%		84.2%	0.8%
	5	Both	0.6%	0.5%	80.3%	2.3%	14.9%	1.5%	0.0%	8.4%	38.4%	1.8%	28.8%	22.6%	0.0%	5.6%	78.2%	2.3%	7.4%	6.6%
		Female	1.2%	0.5%	28.0%		40.1%	30.2%	0.3%	1.8%	75.4%		22.5%	0.0%	0.2%	1.3%	58.5%		39.9%	0.0%
		Male	3.2%	4.0%	86.3%		5.2%	1.2%	78.1%	2.1%	19.7%		0.1%	0.1%	33.6%	0.0%	0.9%		63.1%	2.4%
	15	Both	0.3%	0.1%	62.4%	0.4%	24.6%	12.1%	0.3%	6.5%	83.2%	0.6%	6.0%	3.4%	28.2%	0.1%	28.3%	2.1%	38.5%	2.8%
		Female	0.5%	0.0%	10.6%		85.4%	3.4%	0.3%	1.6%	52.6%		41.9%	3.5%	0.6%	3.6%	82.3%		12.7%	0.8%
		Male	3.5%	1.2%	55.1%		9.1%	31.1%	67.2%	2.0%	26.2%		0.0%	4.7%	49.2%	0.0%	0.8%		49.0%	0.9%
	25	Both	3.9%	24.7%	10.9%	27.5%	6.9%	26.1%	0.2%	9.3%	78.0%	5.5%	4.0%	2.9%	0.0%	4.5%	16.1%	69.4%	0.5%	9.5%
		Female	1.9%	0.6%	34.8%		43.3%	19.5%	0.8%	0.3%	62.4%		30.2%	6.3%	0.1%	0.5%	23.3%		76.1%	0.0%
		Male	7.1%	1.0%	80.6%		11.3%	0.0%	69.2%	2.0%	24.8%		0.0%	3.9%	52.3%	0.0%	0.5%		46.4%	0.7%
	35	Both	10.5%	32.1%	29.2%	13.9%	12.6%	1.7%	0.0%	4.9%	72.5%	22.6%	0.0%	0.0%	0.0%	16.4%	79.6%	0.6%	3.0%	0.4%
		Female	2.4%	0.2%	42.5%		51.8%	3.0%	0.3%	1.4%	84.0%		14.3%	0.0%	0.7%	4.2%	75.8%		18.7%	0.5%
		Male	41.3%	0.0%	36.4%		0.9%	21.4%	0.0%	53.6%	35.8%		7.2%	3.4%	82.2%	0.4%	3.9%		13.2%	0.3%
	45	Both	3.3%	25.2%	8.9%	32.3%	7.5%	22.7%	0.1%	20.7%	4.9%	42.8%	16.5%	15.0%	2.9%	0.5%	6.3%	3.9%	77.2%	9.2%
		Female	2.5%	0.0%	49.5%		40.5%	7.6%	0.6%	1.8%	81.2%		9.7%	6.8%	0.4%	1.7%	74.5%		21.1%	2.3%
		Male	5.2%	0.0%	88.0%		2.3%	4.5%	35.3%	1.8%	20.1%		0.0%	42.8%	45.9%	0.0%	1.9%		39.1%	13.0%
	55	Both	1.3%	18.1%	6.6%	41.2%	5.2%	27.5%	0.0%	9.3%	1.3%	82.6%	3.5%	3.3%	4.9%	0.7%	6.8%	13.3%	72.9%	1.3%
		Female	2.5%	0.2%	50.3%		43.8%	3.2%	0.5%	2.3%	57.1%		39.7%	0.4%	0.3%	1.9%	83.8%		13.9%	0.0%
		Male	45.0%	0.0%	51.7%		1.3%	1.9%	62.5%	2.7%	16.7%		0.0%	18.2%	23.5%	0.2%	2.3%		52.1%	21.9%
	65	Both	0.0%	20.0%	3.5%	63.1%	3.1%	10.3%	0.0%	14.5%	0.1%	55.3%	4.4%	25.8%	0.1%	0.7%	0.7%	1.3%	89.9%	7.3%
		Female	1.2%	20.0%	54.4%		8.9%	15.5%	0.3%	1.2%	73.9%		24.5%	0.1%	3.8%	1.3%	40.9%		20.2%	33.8%
		Male	4.1%	0.0%	58.2%		0.3%	37.4%	58.2%	3.5%	22.3%		0.4%	15.6%	49.4%	0.0%	2.3%		35.6%	12.6%
	75	Both	0.0%	0.4%	0.1%	54.9%	29.8%	14.7%	0.4%	2.1%	3.8%	52.2%	38.5%	3.0%	2.9%	9.2%	20.4%	9.6%	35.5%	22.6%
		Female	0.2%	43.2%	7.7%		0.0%	48.9%	0.3%	0.5%	48.4%		31.5%	19.3%	1.6%	9.7%	27.0%		61.0%	0.7%
		Male	6.9%	0.0%	79.9%		1.9%	11.3%	77.4%	1.8%	11.3%		0.1%	9.4%	33.0%	1.6%	17.1%		3.9%	44.4%
	85	Both	16.5%	9.4%	2.8%	12.2%	29.8%	29.3%	1.2%	3.6%	4.4%	74.0%	9.5%	7.2%	3.9%	8.3%	2.0%	31.3%	11.0%	43.5%
		Female	23.8%	1.1%	24.0%		13.7%	37.4%	0.2%	0.5%	0.9%		88.6%	9.9%	13.5%	2.8%	44.5%		7.9%	31.3%
		Male	62.0%	0.2%	25.4%		12.0%	0.5%	75.0%	0.4%	17.9%		0.0%	6.7%	4.3%	0.5%	66.5%		13.0%	15.7%

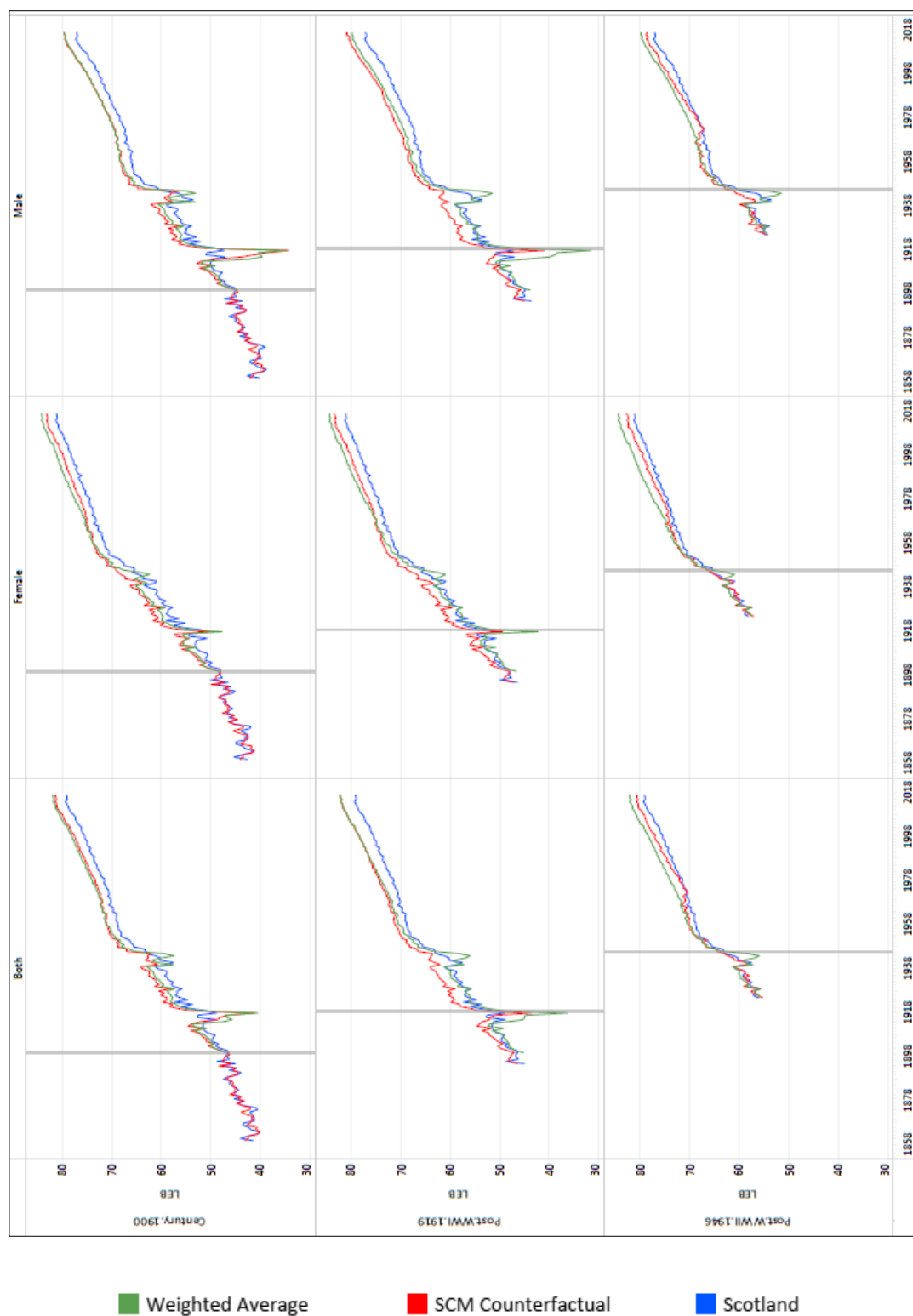
This table reports the covariate weights generated by each synthetic control model, organised by breakpoint model, age group, and sex. Each column represents a covariate included in the model; darker blue cells indicate larger weights, lighter blue reflect smaller contributions, and blank cells show where no weight was assigned. As with the country weights, most models place substantial weight on a small number of covariates, highlighting which variables primarily drive model fit.

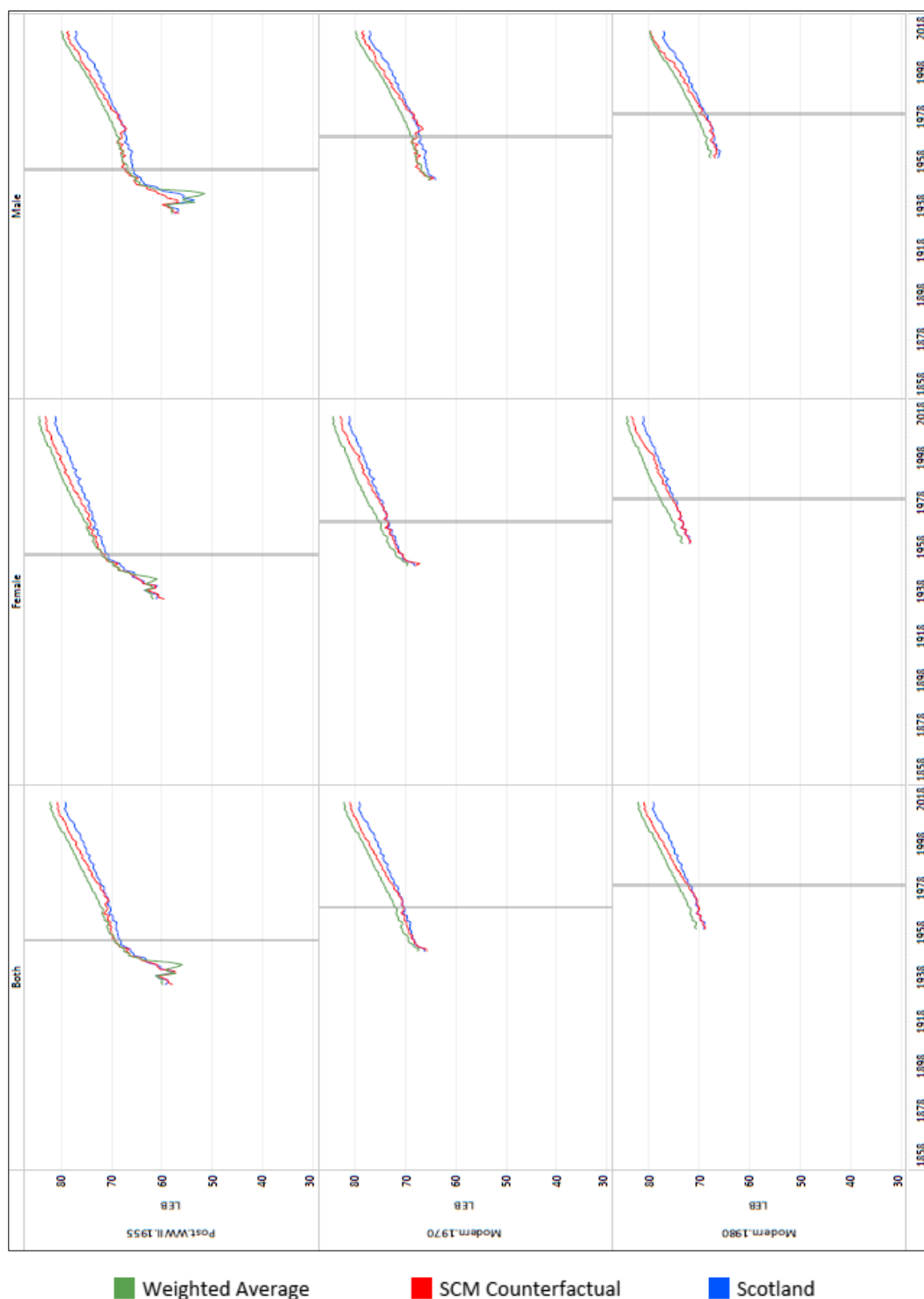
Figure 1.15: Fixed Basket Weighted Averages and Model Specific (Countries Available) Weighted Averages with Scotland's Actuals



Note: Model specific weighted averages are based on the population of the countries that are available for a specific date range and thus included in the model. Additionally, the “fixed country weighted averages” is shown, which are based on nine countries with data originating at or before 1900. Any remarks in reference to the non-model specific weighted average are based on these seven countries.

Figure 1.16: SCM Result Trends for the All-Ages Models





Note: Each panel shows life expectancy at birth over time for Scotland, the weighted average, and the synthetic control counterfactual for the given model with the breakpoint (potential treatment) marked by a gray line. Results are shown separately for total, male, and female populations. Divergences between the lines highlight how the model performs.

Figure 1.17: Differences in Scotland's Actual LEB vs the SCM Estimate and the Weighted Average in 2017 by Age, Sex and Model

		2017																	
		Both						Female						Male					
Diff from Synthetic Scotland	All Ages	-2.24	-3.15	-1.50	-1.56	-1.84	-1.88	-2.03	-2.25	-1.54	-2.01	-1.80	-2.36	-2.47	-3.72	-1.48	-1.46	-1.25	-2.59
	1	-2.26	-3.57	-1.78	-1.67	-2.14	-2.51	-2.10	-2.33	-1.70	-1.55	-2.08	-2.56	-2.45	-2.71	-1.92	-1.95	-2.59	-2.64
	5	-2.40	-4.00	-2.16	-1.75	-2.02	-2.11	-2.32	-3.13	-1.83	-1.87	-2.14	-2.55	-2.46	-2.22	-2.04	-2.04	-2.27	-2.66
	15	-2.32	-3.67	-2.17	-1.50	-1.37	-2.55	-2.38	-3.58	-1.73	-2.15	-2.25	-2.53	-2.46	-3.73	-2.51	-2.05	-2.27	-2.63
	25	-2.25	-2.18	-2.14	-1.20	-1.40	-1.56	-2.06	-3.48	-1.73	-2.07	-2.45	-2.47	-2.45	-3.75	-2.19	-2.09	-2.25	-2.64
	35	-2.19	-2.09	-1.64	-1.85	-1.51	-1.36	-2.00	-3.30	-1.66	-2.15	-2.32	-2.41	-2.29	-3.02	-1.57	-2.26	-1.35	-2.33
	45	-1.91	-2.62	-1.58	-1.72	-1.21	-1.63	-1.75	-1.81	-1.42	-1.78	-2.11	-2.12	-1.76	-1.86	-2.60	-1.93	-1.94	-1.83
	55	-1.67	-1.67	-1.14	-1.46	-1.20	-1.37	-1.54	-1.87	-1.27	-1.64	-1.81	-1.75	-1.54	-1.50	-1.54	-1.52	-1.40	-1.36
	65	-1.17	-1.42	-1.22	-0.96	-1.12	-1.01	-1.29	-1.38	-1.01	-0.95	-1.43	-1.44	-1.18	-1.32	-1.35	-1.32	-1.16	-0.93
Diff from Weighted Average	All Ages	-2.77	-3.01	-3.01	-3.01	-3.01	-3.01	-3.01	-3.23	-3.23	-3.23	-3.23	-3.23	-2.52	-2.75	-2.75	-2.75	-2.75	-2.75
	1	-2.80	-2.98	-2.98	-2.98	-2.98	-2.98	-3.04	-3.21	-3.21	-3.21	-3.21	-3.21	-2.55	-2.72	-2.72	-2.72	-2.72	-2.72
	5	-2.81	-2.99	-2.99	-2.99	-2.99	-2.99	-3.06	-3.23	-3.23	-3.23	-3.23	-3.23	-2.55	-2.73	-2.73	-2.73	-2.73	-2.73
	15	-2.84	-3.02	-3.02	-3.02	-3.02	-3.02	-3.11	-3.26	-3.26	-3.26	-3.26	-3.26	-2.55	-2.74	-2.74	-2.74	-2.74	-2.74
	25	-2.75	-2.96	-2.96	-2.96	-2.96	-2.96	-2.94	-3.14	-3.14	-3.14	-3.14	-3.14	-2.56	-2.75	-2.75	-2.75	-2.75	-2.75
	35	-2.65	-2.85	-2.85	-2.85	-2.85	-2.85	-2.96	-3.15	-3.15	-3.15	-3.15	-3.15	-2.33	-2.53	-2.53	-2.53	-2.53	-2.53
	45	-2.33	-2.51	-2.51	-2.51	-2.51	-2.51	-2.70	-2.88	-2.88	-2.88	-2.88	-2.88	-1.94	-2.12	-2.12	-2.12	-2.12	-2.12
	55	-2.06	-2.19	-2.19	-2.19	-2.19	-2.19	-2.52	-2.65	-2.65	-2.65	-2.65	-2.65	-1.59	-1.69	-1.69	-1.69	-1.69	-1.69
	65	-1.94	-1.96	-1.96	-1.96	-1.96	-1.96	-2.32	-2.34	-2.34	-2.34	-2.34	-2.34	-1.51	-1.50	-1.50	-1.50	-1.50	-1.50
	75	-1.42	-1.40	-1.40	-1.40	-1.40	-1.40	-1.69	-1.68	-1.68	-1.68	-1.68	-1.68	-1.10	-1.05	-1.05	-1.05	-1.05	-1.05
	85	-0.74	-0.64	-0.64	-0.64	-0.64	-0.64	-0.92	-0.81	-0.81	-0.81	-0.81	-0.81	-0.44	-0.34	-0.34	-0.34	-0.34	-0.34
		Century.1900	Post.WWI.1919	Post.WWII.1946	Post.WWII.1955	Modern.1970	Modern.1980	Century.1900	Post.WWI.1919	Post.WWII.1946	Post.WWII.1955	Modern.1970	Modern.1980	Century.1900	Post.WWI.1919	Post.WWII.1946	Post.WWII.1955	Modern.1970	Modern.1980

Note: This figure displays the difference between Scotland's actual 2017 life expectancy and two benchmarks: the synthetic control estimate and the weighted average for the model's available countries. Negative values indicate that Scotland's actual life expectancy was lower than the benchmark for that age, sex, and model. Each section represents a comparison of values across the six models by measure, sex and age. Bar shading reflects the rank of the absolute difference, with darker blue indicating larger deficits and lighter shades indicating smaller gaps.

Death and Taxes: Did Tax Undercutting in Ireland Result in Lower Economic Growth and Lower Mortality?

Abstract

Since the 1980s, many developed nations have lowered their statutory corporate tax rate to encourage foreign investment to promote economic growth. However, few countries have implemented rate reductions as drastic as the Republic of Ireland. In 1997, Ireland passed the Tax Consolidation Act (TCA), which accelerated rate declines. They reached a low of 12.5% in 2003, the lowest rate in Western Europe. This low tax rate was reinforced by permissible base erosion and profit shifting (BEPS) strategies. This led to the establishment or expansion of many multinational enterprises (MNEs) in Ireland and rapid economic growth. Nevertheless, critics argue that the low-tax environment did not result in substantive development or tangible benefits for the Irish population.

This study applies the Synthetic Control Method (SCM) to assess the impact of corporate tax rate reductions on aggregate economic measures. The findings demonstrate that both FDI net inflows per capita and GNI (PPP-adjusted) per capita increased compared to the synthetic counterfactual, reflecting a significant change in Ireland's economic trajectory during this period. Considering the established link between economic conditions and population health, the analysis also evaluates trends in mortality. Although mortality rates improve relative to the counterfactual over time, these improvements are more gradual and display greater variability, indicating a more indirect and less clearly attributable relationship.

Overall, the findings indicate that Ireland's economic outcomes diverged markedly from a plausible counterfactual following the period of corporate tax undercutting, while changes in health outcomes are more ambiguous and likely reflect the interaction of economic expansion with a broader set of structural and institutional factors.

1 Introduction

For several decades, many Western European countries have reduced corporate tax rates as a means of attracting foreign direct investment (FDI) and stimulate economic growth. This strategy has been increasingly effective as non-tax cost barriers to the location decisioning of multinational enterprises (MNEs) have diminished due to advances in transportation, technology, and communication, as well as the liberalization of trade. Consequently, corporate tax rates play an increasingly critical role for countries seeking to attract foreign firms. At the firm level, lower corporate tax rates increase after-tax profits and reduce the cost of capital, potentially supporting greater investment and innovation (Gechert & Heimberger, 2022).

Still, the efficacy of corporate tax cuts as a driver of national economic growth remains a topic of ongoing debate. Traditional theoretical frameworks generally posit that corporate taxes inhibit economic growth and innovation and that lower tax rates promote investment and productivity (Judd, 1985; Chamley, 1986; Gechert & Heimberger, 2022; Kehoe, Chari, & Atkeson, 1999). However, other researchers have challenged these conclusions, arguing that the relationship between taxation and growth is sensitive to the underlying model assumptions and may thus be incomplete or context-dependent (Chen, Chu, Chu, & Lai, 2017; Ferraro, Ghazi, & Peretto, 2020; Straub & Werning, 2020).

Empirical evidence provides more unified support for the growth-enhancing effects of corporate tax reductions, with many studies finding increases in FDI, productivity and overall economic output following rate declines (Simmons, 2003; Bénassy-Quéré, Fontagné, & Lahrière-Révil, 2005; Wijeweera, Dollery, & Clark, 2007; Sato, 2012; Becker, Fuest, & Riedelc, 2012; Abdioğlu, Biniş, & Arslan, 2016; Lee & Gordon, 2005; Romer & Romer, 2010; Shevlin, Shivakumar, & Urcan, 2019; Veronika & Lenka, 2012). Still, the broader economic tradeoffs remain contested. Corporate tax cutting's impact on unemployment in both the short- and long-run horizons is disputed (Halko, 2005; Smith E., 1994; Parai, 1999; Keuschnigg, 2009; Cerda & Larrain, 2010). Additionally, many have concluded that inequality has increased in low tax states and that MNEs are

disproportionately advantaged relative to domestic firms (Halko, 2005; Smith E. , 1994; Parai, 1999; Keuschnigg, 2009; Cerda & Larrain, 2010).

Despite this extensive body of research, relatively few studies have examined the longer-term implications of large-scale corporate tax reductions, particularly in cases where countries pursue aggressive tax undercutting strategies rather than incremental rate changes. Moreover, the literature has largely focused on conventional economic outcomes, with less attention given to broader measures of economic welfare. Ireland provides a particularly compelling case in this context. The 1997 Tax Consolidation Act (TCA) represents one of the most pronounced episodes of corporate tax undercutting among developed economies. The Act accelerated the already decreasing corporate tax rate in the Republic of Ireland – reducing the statutory rate from 36% in 1997 to only 12.5% by 2003. This lower rate undercut all other countries in Western Europe and has remained the second lowest in the OECD (next to Hungary) ever since. This is paired with the fact that, until recently, Ireland’s tax code permitted several base erosion and profit shifting (BEPS) techniques, which meant that the effective tax rate was even lower.

In this study, we examine how Ireland’s economic and population-level outcomes evolved following this period of substantial fiscal undercutting. Specifically, we evaluate changes in (i) FDI net inflows per capita, (ii) purchasing price parity (PPP), adjusted gross national income (GNI) per capita, and (iii) mortality rates. While FDI and GNI provide insight into aggregate economic performance¹⁶, they do not fully capture how economic gains translate into broader societal outcomes. In particular, Ireland’s role as a tax-efficient jurisdiction raises

¹⁶ GNI PPP per capita offsets some of the limitations of using measures such as GDP and adjusts for price differences. While both FDI net inflows and GNI PPP offer insight, they do not fully capture the costs and benefits to the Irish citizens. Ireland is largely regarded as a tax haven. Some MNEs have only relocated to Ireland “on paper” and have not increased employment in the country at any significant level. As these firms have engaged in BEPS strategies, their Irish tax liabilities (and thus tax revenue) have been limited. FDI and GNI PPP are still limited in revealing the amount of wealth that is created and the positive or negative impacts to the population at large.

questions about the extent to which observed economic growth reflects real domestic activity versus financial structuring by multinational firms.

To address this, we incorporate mortality as a summary measure of population health, the analysis extends the evaluation of corporate tax policy beyond standard economic indicators. Furthermore, rather than isolating a single causal mechanism, the paper assesses how a period of substantial fiscal undercutting, occurring alongside broader structural changes, corresponded with shifts in both economic and population-level outcomes. Thus, the inclusion of mortality allows us to extend the analysis beyond conventional economic indicators and consider broader implications for population well-being.

We perform this analysis using the synthetic control method (SCM). SCM enables us to generate a better proxy for Ireland prior to the rate change based on a weighted average of other Western European countries. This in turn leads to more stability and control for unobservable country-level differences as compared to other techniques that are often employed for similar tax rate policy change analysis, such as difference-in-difference (DiD).

The results indicate that FDI and GNI were both positively affected by the TCA even beyond prior downward trends in taxes and previous open trade strategies in Ireland. Furthermore, we find that FDI and GNI increased relative to the synthetic counterfactual following the reform. Finally, improvements in mortality rates that coincide with this period of economic expansion are observed. While these patterns are consistent with the broader economic transformation associated with Ireland's tax strategy, they likely reflect the combined influence of multiple concurrent structural changes. While the the SCM framework helps identify divergence from the counterfactual trajectory, it does not isolate a single causal mechanism among the overlapping policy, institutional, and global economic factors present during this period.

2 Existing Literature

Studies on the outcomes of corporate tax reductions have proliferated as rates have been reduced. While some economic theory and empiric time-series studies date back to the early 1980s, most of the research has been conducted within the last three decades. Overall, the theoretical framework suggests that corporate tax cuts have a long-run positive relationship with output. Unlike income tax reductions, which theoretically only have short-run output gains, corporate tax cuts reduce capital constraints and enable R&D investment. This yields long-run growth.

Still, these outcomes are not universally agreed upon. The neoclassical theoretic literature regarding the impact of corporate taxation is very divided and based heavily on the parameters used in each study.¹⁷ First, several studies imply that corporate tax constraints raise the cost of capital (K), and capital accumulation is restricted, which in turn leads to output declines in a neoclassical growth model. In tandem, labor efficiency loss occurs due to poor allocation of resources and a loss in total factor productivity (TFP) (Judd, 1985; Chamley, 1986; Gechert & Heimberger, 2022; Arnold, et al., 2011). In Judd (1985), Chamley (1986), and Kehoe et al. (1999), the authors determine that the optimal rate would be zero. While Judd and Chamley do so under a limited set of conditions and constraints, Kehoe and his coauthors also determine that rates are optimally zero while assuming a heterogeneous population, open economy, endogenous growth, continuous birth rates, and overlapping populations. Still, other theoretical frameworks have challenged these findings and determine non-

¹⁷ To some degree, the generalized theoretical frameworks for taxation and the outcomes to net savings, aggregate demand, aggregate supply, and production can be applied if taxation costs are passed to the consumer. Empirical research had suggested this is at least partially true (Fuest, Peichl, & Siegloch, Do Higher Corporate Taxes Reduce Wages? Micro Evidence from Germany, 2018; Baker, Sun, & Yannelis, 2020). Fuest et al. (2018) determined that about half of corporate tax increases are passed to workers via wage reductions, and Baker et al. (2020) find that prices increase by about 0.17% and corporate taxes climb by 1%. Still, it is important to practice caution when applying generalized tax models to corporate taxation as tax structures yield different decision-making strategies amongst firms and households (Shevlin, Shivakumar, & Urcan, 2019; OECD, 2010). Additionally, low tax rates in one area of the economy often results in higher alternative taxes, so preferred taxation strategies must be understood.

zero rates are not optimal or a logical steady-state. Even using the same assumptions as Judd (1985), Straub & Werning (2020) suggest that zero tax convergence is slow and only occurs when the intertemporal elasticity of substitution exceeds one. Otherwise, non-zero capital taxes are optimal. Additionally, Aghion et al. (2013) introduce a Schumpeterian growth model (i.e., R&D results in productivity enhancing innovation) to Chamley and Judd's frameworks. The study concludes that a zero-capital tax rate is not an optimum, due to increases in the taxation of labor. This results in a shrinkage of the labor supply that is required for innovation.

Many empirical studies focus on the topic of growth as well, namely exploring the impacts of rate changes on FDI, GDP, or the productivity of labor. Studies looking at the relationship between rate adjustments and FDI specifically have expanded methodologically since first appearing in the 1980s. Early papers, such as Hartman (1984) and Slemrod (1990), used a time series approach. As they were limited in geographic scope, only weak evidence is found for the relationship between corporate taxes and net inflows. Most of the more recent studies have used cross-sectional or panel datasets to observe the impacts of corporate tax rate changes across multiple spatial groups (Simmons, 2003). Chennells & Griffith (1997) build upon early methods by observing the impact of the effective marginal tax rate (EMTR) and the effective average tax rate (EATR) across ten countries, which arguably better reflects revenues and firm liabilities.¹⁸ While the data used in the study concludes in 1994, their results suggest that corporate taxation decisions are a principal consideration of FDI location selection. Several studies have confirmed these findings, determining that FDI have a significant inverse relationship to the

¹⁸ Across various studies that utilize alternatives to the statutory tax rate, such as the effective marginal tax rate (EMTR) and the effective average tax rate (EATR), there is variability. Some estimate that the effective tax rate is very low relative to the statutory rate for Ireland Chennells & Griffith, 1997; Stewart J. , 2011 (Chennells & Griffith, 1997; Stewart J. , 2011). Spengel et al. (2020) enlists a method used in Devereaux & Griffith (2003) to derive these measures. The data suggests that the EMTR and EATR rose between 1998 and 2003 from roughly 7.9% and 9.4% to 13% and 14.3% respectively. These rates are higher than the statutory rate, as they also include revenue from passive income, which is taxed at 25% today. Likely, the EMTR and EATR have converge closer to the statutory rates as BEPS strategies and loopholes have closed. Still, public long-term, cross-sectional data is limited.

corporate tax rate (Simmons, 2003; Bénassy-Quéré, Fontagné, & Lahrèche-Révil, 2005; Wijeweera, Dollery, & Clark, 2007; Sato, 2012; Becker, Fuest, & Riedelc, 2012).

Empirical evidence also suggests that long-term growth occurs following rate adjustments, though the magnitude of the impact is debated. Lee and Gordon (2005) find that a 10% reduction in corporate taxes increases growth by $\approx 1.2\%$, while Romer & Romer (2010) conclude that GDP growth is robustly negatively affected by tax increases, especially when considering lags. Ferede & Dahlby (2012) conclude that a 1% reduction in the corporate tax rate can be associated with a 0.1% - 0.2% increase in the annual growth rate. Shevli et al. (2019) and Veronika & Lenka (2012) find evidence of a strong, negative relationship. Several papers have found that corporate taxation is harmful for growth as a tax strategy relative to consumption and income taxes (Arnold, et al., 2011; Johansson, Heady, Arnold, Brys, & Vartia, 2008; OECD, 2010; Lee & Gordon, 2005). Finally, in Mertens & Ravn (2013), it is concluded that changes in the tax rate have rapid output effects.

Other economic theory regarding corporate taxation focuses on aggregate decision making and preference shifting. Several endogenous growth theory papers have sought to determine how rate changes impact R&D spending, innovation, and entrepreneurship (Gechert & Heimberger, 2022). Both Ohn (2018) and Chen et al. (2017) agree that innovation and R&D are restricted by capital taxation, but Chen et al. (2017) finds that consumption impacts occur only in the short run. In the long-run, due to tax-shifting effects, growth occurs. However, Ferraro et al. (2020), conclude differently finding that corporate tax reductions lead to increased competition, or entrants in the market, but R&D and thus quality, innovation, and growth decreases (Ferraro, Ghazi, & Peretto, 2020). Still, some empirical evidence suggests that firm do increase innovation and R&D spending when tax liabilities diminish (Mukherjee, Singh, & Žaldokas, 20017; Rao, 20016).

Economists have also sought to examine the incidence of corporate taxation on unemployment and wages though findings are not consistent. In terms of unemployment, Wang (1993) determines that the effect of a rate change is felt mostly on the capital side. However, as wages are above the market-clearing price for the private

sector, a rate increase results in a movement out of the corporate sector. Thus, unemployment declines (Wang, 1993). Still, many theoretic and empiric studies have challenged these conclusions and have shown that rate increases do lead to greater unemployment in the longrun (Zirgulis & Šarapovas, 2017; Feldmann, 2011; Parai, 1999; Bettendorf, Horst, & Mooij, 2009; Keuschnigg, 2009; Smith E., 1994). Bettendorf et al. (2009) focuses on countries in the European Union and find that increases in the corporate tax lead to high unemployment with variation across countries, with the highest level variance in countries, such as Ireland, where there is a high number of MNEs and combined with a low level of substitution between capital and labor.

Several papers examine the relationship of wages and corporate taxes though results are divided. Hassett and Mathur (2006) and Arulampalam (2012) both conclude that wages are strongest when rates are low. Hassett and Mathur (2006) focus specifically on wage outcomes. They conclude that wages are highly responsive to the changes in the corporate tax rate, especially in smaller economies. Arulampalam (2012) estimates the elasticity in a bargaining framework using firm level data from nine European countries. The long-run elasticity implies that about half of the tax burden is assumed by labor in the form of wage reductions. Still, some have challenged this finding. Gentry (2007) reviews Hassett and Mathur (2006) within a general equilibrium model and instead finds that labor does shoulder some of the burden of corporate tax rate reductions. Gentry argues that general equilibrium models may prove more useful than empirical studies, which have to rely on aggregated data and measures that are largely influenced by several macroeconomic variables.¹⁹ Gravelle & Hungerford (2008) also challenged popular empirical findings suggesting that both theoretic and data driven results imply that labor does *not* shoulder the impact of increased corporate taxes. They argue that empirical studies showing this relationship

¹⁹ Gravelle (2011) outlines this debate regarding wage elasticity and corporate tax rates amongst the theorists and empiricists.

“suffer from econometric problems.” Other notable conclusions are drawn as well, such as that revenue should not fall following corporate tax increases, but economic distortions are likely (Gravelle & Hungerford, 2008).

Lastly, there is a strand of literature concerning the impacts on inequality and welfare that result from rate reductions. Nallareddy et al. (2022), find that income inequality increased as a result of corporate tax cuts. Hager & Baines (2020) too conclude that the increasing regressivity of taxation can lead to firms being less prone to engage with investments with indirect benefits to their employees and more prone to those that benefit shareholders. Inturn, this leads to widening inequality.

Despite the large amount of research on these measures, few studies have yet to be conducted on the indirect or ancillary impacts of corporate tax rate reduction. Outcomes, such as investment in healthcare, public health, disaster relief or public programs, are also likely outcomes from such fundamental fiscal policy. Corporate taxation impacts budgets; thus, funding for healthcare, welfare, and programming can increase in some systems.

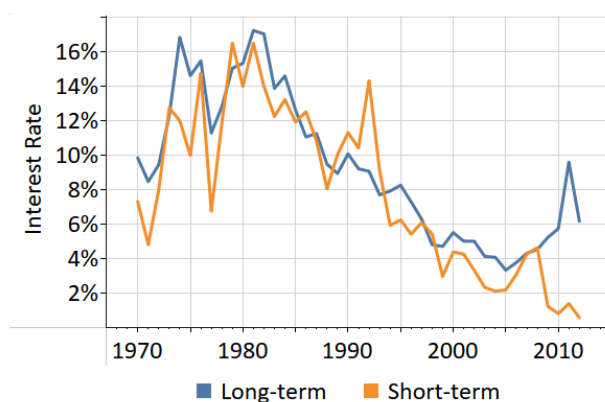
3 Background

Rate reductions in Western Europe were not introduced uniformly in the 1980s and 1990s but popularised as a means of attracting MNEs from countries that did not reduce their statutory rates at the same pace, such as the United States. The United Kingdom had reduced rates in the mid-1980s and remained below most countries for several years. While slower than some to commence rate reductions, Ireland’s TCA rapidly accelerated decreases and outpaced all other countries in Western Europe. Paired with permitted BEPS strategies, the government was betting on FDI and economic expansion to offset revenue loss. This was a bet that they had lost before albeit under different economic circumstances.

Prior to joining the European Union in 1973, Ireland had struggled to benefit from the periods of growth experienced by neighboring countries or to foster an open trade economy (O’Rourke, 2017). Some early efforts were made to incentivise globalization and international trade, such as the founding of an Export Profits Tax

Relief (EPTR) scheme in 1956. The EPTR provided tax concessions on company's exports (Barry, 2011). Additionally, in 1959, the Shannon Free Zone (SFZ) was established.²⁰ These efforts were effective but not transformative for the Irish economy, which struggled to prevent outward migration. It was not until 1970 that efforts to end protectionism took hold and net migration turned positive (Kelleher, 2013; Whelan, 2011). After joining the EU in 1973, educational standards increased and free trade policies expanded (Whelan, 2011).

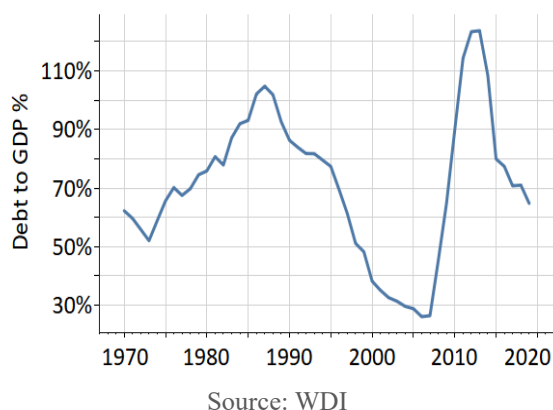
Figure 2.1: Est. Interest Rates in Ireland, 1970 – 2012



Source: Gerlack & Steward, 2014

Note: The blue line shows long-term interest rates and the orange line shows short-term interest rates over time.

Figure 2.2: Debt to GDP % in Ireland, 1970 - 2019



Source: WDI

Note: The line represents Ireland's annual debt-to-GDP ratio, illustrating its fluctuation across the full observation period.

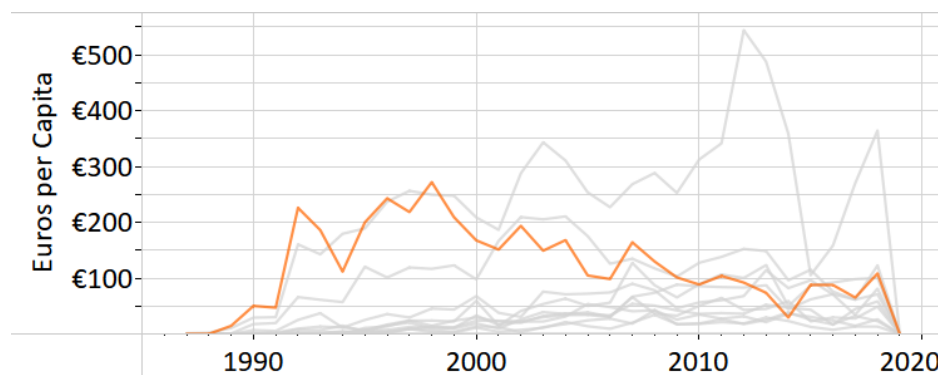
Corporate taxes remained flat in Ireland until 1988 for both trading and passive income before the legislatively driven rate reductions commenced. The corporate tax rate moved inversely to income and consumption rates. Between 1988 and 1990, the statutory rate fell from 50% to near 40%, and certain tax cuts and exemptions were implemented in efforts to prop up specific sectors. Another significant change was the extension of the 10% manufacturing rate to the International Financial Services Centre (IFSC) in 1987 and other

²⁰ This small "free trade zone" offered special customs rules and tax incentives for the businesses that operated within its 600-acre boarder. The SFZ was the first of its kind globally, though other countries would establish similar industrial park free-trade zones afterwards (Farole, 2011).

special economic zones, including the Shannon Airport (Walsh & Sanger, 2014). More substantially, in 1987, the tax rate on financial services was set to 10% (Noonan, 2013). These policies immediately led to inconsistent interpretations of tax rules, and several legal challenges ensued.

The efforts made in the late 1980s were tepid compared to the free-trade, low-tax policies that followed, but the seeds of the Celtic Tiger had been sown. The economy began to improve. GDP grew steadily; net migration began to rise again, and female participation in the labor market continued to climb. Competition targeting strategies also emerged, evidenced by the deregulation of and subsequent competition in the telecommunications sector (McAleese, 2000).²¹ Additionally, the European Single Market was formed in 1993. While 31 nations would participate by the following year with the introduction of the 1994 Agreement on the European Economic Area (EEA), Ireland was amongst a small cohort of only 12 initially (Bublitz, 2018). Ireland benefited greatly from the EU payments in the years that followed, especially in 1993. [See Figure 2.3.]

Figure 2.3: EU Cohesion Fund Payments to Ireland, 1985 - 2019



Note: The orange line represents Ireland's payments received from the EU Cohesion Fund. The gray lines in the background represent other EU member states, allowing for visual comparison of Ireland's relative position.

²¹ In 1980, the telecom industry was highly regulated and one of the poorest performing in Western Europe, especially as other countries liberalized telecom as the US had done previously. Improvements had been made throughout the 1980s, but competition only proliferated following European Commission led efforts in the early 1990s. By 1995, the telecom market started experiencing several new entrants. The new competition promised better pricing, coverage, and stability for all on the island, including potential MNEs in other sectors (Burnham, 2003; Mayer-Schönberger & Strasser, 1999).

By 1995, Ireland was well poised competitively. Growth was apparent and indirect measures, such as public health, had improved greatly since the 1970s. Already, mortality rates placed Ireland in the lowest quartile in Western Europe and were significantly below the United Kingdom's for both males and females. Still, lawmakers wanted to affirm Ireland's competitive advantage, and FDI had risen only marginally. Additionally, the EU was pressuring the Irish government to discontinue the 10% special taxes on manufacturing and financial services. While rates had been reduced between 1987 and 1996 periodically, Ireland was not yet an outlier. The "headline" rate remained above the UKs, though – as discussed - much of the tax infrastructure allowing for BEPS was already in place. In fact, the US has associated Ireland with base erosion since the early-1980s (Gordon, 1981). Still, new arbitrage opportunities opened the MNEs with the lowering of the statutory rate and the provisions of the 1997 Tax Consolidation Act. The act asserted that the profit tax would change to 32% in 1998, would decline by 4% per year until 2002, and then fully phase in at the 12.5% rate by 2003 (Revenue, 1997; Irish Statute Book, 1997).²² This would significantly undercut the UK's rate by 1999 and almost all others by 2000.

In the years since, MNE's have proliferated in Ireland and FDI has climbed considerably. Technology firms, such as Google, Apple, and Facebook, have been given specific attention due to their large sizes and prominence. Still, note that about half of the jobs created by foreign firms are in the manufacturing space (Department of Finance, 2014).

Following the TCA, other measures improved as well. On average, gross national income (GNI) rose, though not in parity with GDP. Additionally, gross and fixed capital formation expanded. Net migration too continued to climb until 2006. Unemployment reached a low rate of under 4% in 2000. Additionally, average wage growth exceeded inflation. Wages remained constrained but have still surpassed those in the UK. Wage

²² An alternative rate of 25% on specific forms on interest and capital gains, royalties, rental income and some miscellaneous was also established (Revenue, 1997).

growth also resulted in elevated consumer spending. With greater disposable income, quality-of-life improvements for the Irish followed, including increased travel. Despite rate reductions, overall revenues (including those from corporate taxes) increased enabling investment in several other programs as well.

Healthcare expenditures grew, for example, as mortality rates fell far below any other country in Western Europe. Improvements in preventative and reactive treatment for cardiovascular diseases have propelled many of these gains (Bennett, et al., 2006; Kabir, et al., 2013). Additionally, decreases in smoking have resulted in fewer respiratory infections. However, some of these gains have been tempered by increases in other consumption driven risk factors, such as growing prevalence of diabetes and obesity. [Refer to Figure 2.24 and Figure 2.25 in the appendix.] These advancements and improving mortality rates eventually materialised in life expectancies, which rose from amongst the lowest in Europe to middling (amongst many high tax countries). [Refer to Figure 2.20 in the appendix.]

The bust matched the boom; Ireland was impacted extensively by the 2008 financial crisis. The duration of the recession was longer than most other European countries (roughly four years). Unemployment reached higher levels and remained elevated much longer than in the UK (and still lags UK levels). Net migration turned negative in 2009 and took five years to recover. The IMF and EU eventually partnered to provide a bailout package for Ireland. Still, many of the pre-recession metrics recovered and surpassed 2006-7 levels. Currently, Ireland remains economically strong and relatively healthy. GDP remains elevated above Ireland's nearest neighbors, and mortality rates remain dramatically under the average. Many MNEs have increased their presences in Ireland, though BEPS rollbacks in the 2010s have led to declines in FDI. Additionally, Ireland has committed to adopting the OECD International Tax Agreement, which will set a 15% minimum corporate tax rate for certain MNEs and activities.

4 Data

To best understand how economic conditions, stimulated by the corporate tax change, impacted GNI, FDI, and mortality rates in Ireland, we construct a panel data set from five principal sources. Mortality rates and population values are obtained from the Human Mortality Database (HMD).²³ We age-standardised all mortality rates based on the HMD population counts by age group. In fact, where applicable, the HMD population counts are used to convert other measures into per capita values.

Several economic aggregate measures come from the World Bank's WDI dataset. GDP, GNI, FDI net inflows, and population density are sourced from the WDI API, as well as other metrics, which are not modeled but analysed and visualised. Where applicable, WDI GDP values are used to convert “% of GDP” figures into US dollars. Nominal values alone, such as GDP and GNI, do not account for differences in consumer spending power. Certain markets are notably more expensive than other countries in the data, and costs of living vary from year to year. Additionally, spatial price variation occurs by the type of good or service. Tradables, such as manufactured goods, usually follow the law of one price, while immobile services have higher spatial variation (Tabarrok & Cowen, 2021). To reflect real values rather than nominal, we favor purchasing power parity (PPP) adjusted aggregate measures. WDI does not contain PPP figures prior to 1990. Instead, we impose a scalar that is derived from the ratio of GDP to PPP. This data is obtained from the IMF's World Economic Outlook API.

The rationale for selecting GNI PPP per capita rather than GDP PPP per capita or Ireland's modified GNI (for modeling), is worth noting. In small, open economies, especially for countries that are net recipients of foreign investment and have a high concentration of MNEs, GDP is not an optimal measure. GDP measures the total value of goods and services produced, regardless of whether the income generated from those goods and services

²³ A joint initiative to collect and provide mortality statistics by the Department of Demographics at the University of California, Berkeley (USA) and the Max Planck Institute for Demographic Research (Germany).

goes to domestic or foreign residents. In contrast, GNI measures the total income earned by a country's residents, regardless of whether that income is generated within the nation's borders. However, the value of GNI is also limited as BEPS schemes (such as the relocation of intellectual property (IP) assets to Ireland by MNEs) distort the value of income on the Irish economy. For this reason, the Central Bank of Ireland developed a modified GNI ($\widehat{GNI}$) metric in 2017. While the $\widehat{GNI}$ has been estimated for all years since 1995, historic canned data is not available, and $\widehat{GNI}$ is not available for any countries in our cohort other than Ireland. Still, it is worth noting that $\widehat{GNI}$ remained highly correlated and only slightly lower than GNI until diverging in 2010. Significant separation didn't occur until 2015 long after the tax cuts. For these reasons, we use GNI PPP per capita as the measure for economic growth but note that interpretability of results may be limited for the most recent years.

Unemployment and healthcare spending data is sourced from the OECD. Values for central government debt is derived from IMF data. The only exception was for the Netherlands. Their debt figures are sourced from Statistics Netherlands. The OECD also supplies data on wages, but only for 1990 onward. To estimate wages between 1970 and 1989, Mitchell (1998) is used. Mitchell's data is an estimate for specific industries and thus there is a level of discontinuity between the vectors. Therefore, only the rate of change is used from Mitchell to estimate historic years.²⁴

Data on health risk factors are gathered from the Global Burden of Disease (GBD) study of 2019, which is a multi-national effort to gather such detailed panel data. These variables include healthcare access and quality index (HAQI), universal healthcare coverage (UHCI), body-mass index (BMI), cholesterol, physical activity, alcohol consumption, smoking prevalence and blood pressure (SBP). These measures were selected due to a high association with the improvements in coronary care and infectious lung disease but increases in obesity and

²⁴ Note that some imputation had to occur to generate a continuous cross-sectional data set. A centralized moving average method was used.

diabetes identified in Aabir, et al. (2013) and Bennett, et al. (2006). Additionally, mean temperature is collected from this same data source. The GBD is championed by the Institute for Health Metrics and Evaluation (IHME) at the University of Washington and funded by the Bill and Melinda Gates Foundation.

Modeled taxation values, reflecting the statutory headline rate, are sourced from the Tax Foundation, and verified against legislative documents defined in the text above. Additionally, for analysis and discussion, the effective average tax rates (EATR) and the marginal tax rates (EMTR) are extracted from Spengel et al. (2020). Their paper applies the Devereux/Griffith methodology for deriving these two values.

Other sources were used from single fields. EU payment data is source from the Cohesion Data website. Underlying data is provided the European Commission. CO2 emissions are sourced from the Global Carbon Projects publicly available dataset. Finally, migration statistics are derived from the UN's Departments of Economic and Social Affairs' population dataset.

[See Table 2.1 and Table 2.2 in the appendix for a description and summary statistics for modeled variables.]

5 Methods for Synthetic Control

Synthetic Control Method aids in measuring causal effects of an intervention, such as a change in taxation policy, on an outcome of interest. While most tax change studies have utilised either diff-in-diff or regression approaches, the application of the synthetic control method is particularly versatile for this application.

A primary attractor of SCM is its high level of interpretability. Difference following an event serve as a clear measure of the treatment effect. Compared to DiD, SCM's primary advantage is that it enables a data-driven approach to counterfactual estimation. DiD assumes that the treated and untreated units have similar characteristics in all ways except the treatment. Especially when utilizing country-level aggregate data, this cannot be assumed. Abadie et al. (2010) notes that the standard error in regression reflects uncertainty about aggregate data, but perfect knowledge of aggregate data doesn't fully offset this uncertainty. This is especially true in

comparative case studies, as “an additional source of uncertainty derives from ignorance about the ability of the control group to reproduce the counterfactual of how the treated unit would have evolved in the absence of the treatment” (Abadie, Diamond, & Hainmueller, 2010). SCM minimises the influence of this uncertainty by accounting for time-varying confounders by updating the weights over time (Bouttell, Craig, Lewsey, Robinson, & Popham, 2018; Adhikari & Alm, 2016). Additionally, DiD requires a relatively large sample size to achieve statistical significance and accurately estimate the treatment effect, especially when the outcome variable has high variability. The SCM, however, can be applied to small sample sizes by utilizing the donor pool to construct the synthetic control group - if the pre-treatment outcomes and covariates are well-matched. SCM is generally robust against outliers and unresponsive to noisy data. Country-level datasets are prone to endogeneity problems that occur when variables are omitted. By controlling for unobserved fixed and random effects (“confounders”) over time, the endogeneity problems are reduced (Abadie, Diamond, & Hainmueller, Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program, 2010; Adhikari & Alm, 2016; Abadie, Diamond, & Hainmueller, Comparative Politics and the Synthetic Control Method, 2015).

In SCM, the unit impacted by an intervention is compared to a synthetic counterfactual, which is constructed by assigning weights to potential comparison units. The vector of weights is a combination of the comparison units (also called the donor pool or reference group) and minimises the distance from outcome of the treatment unit in the pre-intervention period. To do so, pre-intervention characteristics (covariates) for each unit are also weighted (Adhikari & Alm, 2016; Abadie, Diamond, & Hainmueller, 2010; Abadie A., 2021). We can express SCM as a dual optimization problem, where both optimal weights for the countries and optimal variable weights are obtained.

In our model, comparison units are drawn from a cohort of 12 other countries in, though some countries had to be excluded from certain models due to a lack of historic data across all measurements.²⁵

If we assign the following:

$$i \in \{J, c_1\}$$

, where $c_1 = \text{Ireland}$

$$J \in \{c_2, c_3, \dots, c_{13}\}$$

$$t \in \{1, \dots, \tau, \dots, T\}$$

, where $\tau = 18$ (aka 1997)

$$T = 39 \text{ (aka 2018)}$$

T contains the 39-year period from 1980 to 2018. We can express the treatment effect, during the post intervention $t_0 + 1, \dots, T$, as...

$$\varphi_{c_1,t} = Y_{c_1,t}^{IRL} - Y_{c_1,t}^U$$

, where $Y_{c_1,t}^{IRL} = \text{Outcome of treated Ireland in } t$

$Y_{c_1,t}^U = \text{Outcome of untreated counterfactual in } t$

$Y_{c_1,t} = \text{Real } Y \text{ in } t$

Since $Y_{c_1,t}^{IRL}$ represents actual outcomes, this can be restated as...

$$\varphi_{c_1,t} = Y_{c_1,t} - Y_{c_1,t}^U$$

²⁵ Switzerland was most often excluded do to only limited historic GNI data.

, where $Y_{c_1,t} = \text{Actual } Y$

Thus, only $Y_{c_1,t}^U$ needs to be estimated using an optimal vector of weights for each unit in J .

$$Y_{c_1,t} = \sum_{c_j} w_{c_j}^* Y_{c_j,t}$$

, where $w_{c_j}^* = \text{weight of county } j$

$$1 \geq w_{c_j}^* \geq 0$$

The weight vector defines the synthetic control and is generator using an optimization procedure.

$$W^* = (w_{c_2}, w_{c_3}, \dots, w_{c_{13}})'$$

Pre-intervention characteristics for Ireland are contained in the $(k \times 1)$ vector X_{c_1} , which is limited to the pre-intervention time. All other countries' characteristics are contained in a $(k \times 12)$ matrix X_J . The optimization must minimise the distance between X_{c_1} and $X_J W$.

In addition to the donor pool weights W^* , a matrix of covariate weights V also needs to be incorporated. These weights are also constrained similarly to W^* . The resulting minimization problem is as follows:

$$\|X_{c_1} - X_J W\| = \sqrt{(X_{c_1} - X_J W)' V (X_{c_1} - X_J W)}$$

The treatment effect can be estimated as...

$$\hat{\phi}_{c_1,t} = Y_{c_1,t}^{IRL} - \sum_{c_2}^{c_{13}} w_{c_j}^* Y_{c_j,t}$$

for $t \in \{\tau, \dots, T\}$.

For a further explanation, see Abadie et al. (2010).

A couple assumptions are made here. First, we assume that the TCA does not have any effect on the donor pool. That is...

$$Y_{it} = Y_{it}^U \text{ if } i \in J$$

Second, it is assumed that there is no anticipation effect, which would shift a portion of the effects prior to 1998. Instead, we assume that any pre-effects are the result of other tax reductions or other variables. While some anticipation effects are possible, given that the legislation was introduced in 1997, they are likely small given the decision making and planning that accompanies relocating (even on paper).

Ideally, the synthetic control group closely matches the trend of the treatment group in the pre-intervention period implying that the counterfactual, or the synthetic Ireland, is a close proxy for Ireland prior to the intervention. The pre-intervention mean-squared prediction error (MSPE) measures the difference of the counterfactual and the treated unit.

Here, MSPE can be expressed as:

$$MSPE_{Pre} = \frac{1}{\tau} \sum_{t=1}^{\tau} \left(Y_{c_1,t}^{IRL} - Y_{c_1,t}^U \right)^2$$

With large values, such as GDP per capita, it can sometimes be useful to examine the root mean-squared prediction error (RMSPE).

$$RMSPE_{Pre} = \sqrt{MSPE_{Pre}}$$

Similarly, $MSPE_{Post}$ and $RMSPE_{Post}$ can be calculated using the post-intervention years $\tau + 1, \dots, T$.

Alone, the $MSPE$ and $RMSPE$ only contain information on the accuracy of the counterfactual to match the untreated trend in the pre- and post-intervention periods. To better assess the frequency at which we'd get similar results devoid of the intervention, placebo tests are used. The same analysis is performed on the untreated

units to determine the frequency that results are obtainable by chance. If placebo tests produce “gaps of magnitude” in the post-intervention period that are roughly the same or better than the SCM then the effect of the treatment is not sufficiently demonstrated (Abadie, Diamond, & Hainmueller, 2010). We perform a placebo test on each of the 12 countries in our donor pool.

Another way to evaluate the placebo effect versus a true treatment effect is to measure the ratio of the *MSPE* or the *RMSPE* from the post- and pre-intervention years.

$$\text{MSPE Ratio} = \frac{MSPE_{post}}{MSPE_{pre}}$$

$$\text{RMSPE Ratio}^{26} = \frac{RMSPE_{post}}{RMSPE_{pre}}$$

As units are not always well matched prior to the treatment, the pre-treatment denominator normalises the *MSPE* and the *RMSPE*. This ensures that the *p*-value is more realistic. Similarly, only placebos that are within some multiple of the *MSPE_{pre}* of the target case will be included. Traditionally, that is a 2x multiple as applied to the mortality rate models here. This process, known as pruning, ensures that placebos that are poorly fitted in the pre-treatment period are excluded.

In cases where the treatment group has very distinctive pre-trends and the covariate fail to explain differences, a close approximation function is not possible and thus the synthetic group cannot serve as a valuable proxy for the treatment group. Post-intervention (or treatment), the synthetic estimate serves as a counterfactual,

²⁶ Alternatively, $\frac{RMSPE_{post}}{MSPE_{pre}}$ is sometimes used as the RMSPE ratio.

which can be juxtaposed against the actuals for the treatment group (i.e., Ireland). The measurable difference between the actual and the counterfactual values (or fitted functions) is the treatment effect.

We run models with different outcome variables. They include FDI net inflows per capita, GNI PPP per capita, and age-adjusted mortality rates. A couple distinctions and characteristics of each model should be noted. First, as mortality rates are modeled by gender, many of the variables are also by gender unless no sex-specific values are available. GNI and FDI models, on the other hand, only contain variables that are not sex specific. Second, not all models include every country due to data availability limitations. Specifically, Switzerland has only limited historic data on GNI, and Switzerland and Portugal have limited data on FDI. Finally, only relevant variables, determined by the Y , are considered in each model. Health risk factors specifically are excluded from models where the Y is an economic measure. In fact, we run mortality rate models with and without health risk factors. Those without the risk factors are titled “simple” models, and those with the risk factors are titled “complex” models.

6 Results and Findings

Results are summarised and discussed below independently for each Y . In all cases, models were stable and were found to be insensitive to parameter adjustments. The best performing optimization for minimizing the pre-intervention MSPE was accepted.²⁷ Most optimization methods yielded nearly identical results, as expected.²⁸

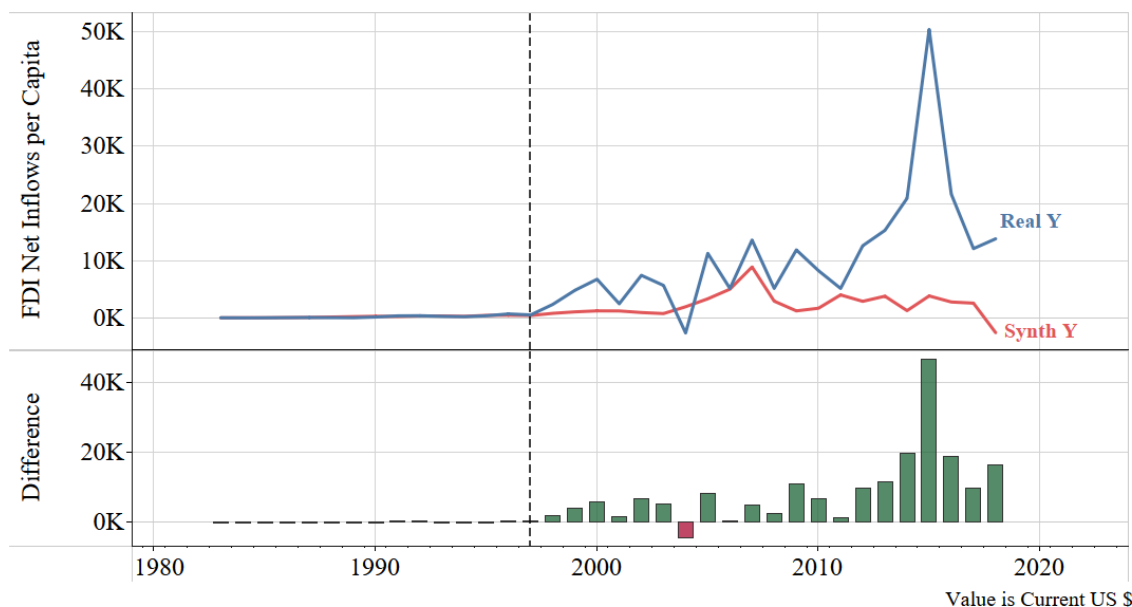
Figure 2.4 illustrates the outcome of the first model on FDI net inflows per capita. The counterfactual suggests that, absent of the rate change legislation, FDI would have climbed only minimally relative to the treated outcome. FDI dropped below zero in 2004 but generally rose steadily through the recession, with a decline occurring only in recent years.

FDI per capita began to rise in 1989 (prior to the TCA); it climbed from about \$35 to near \$720 by 1997 and spiked asymmetrically during select years throughout the pre-intervention period. These spikes are not reflected in the synthetic Ireland $Y_{c_1}^U$, as they did not occur with the same cadence in any non-treated unit. Still, $Y_{c_1}^U$ exemplifies a smoothed trend and approximates the Y_{c_1} well during the pre-intervention.

²⁷ We use three optimization methods that are available in the tidysynth package. They include the Nelder-Mead, the Broyden-Fletcher-Goldfarb-Shanno (BFGS), and a spectral projected gradient method (SPG). Nelder-Mead is a direct search approach where iterative expansion and contraction occurs on the simplex until the value converges on the optimum. It is useful in nonlinear optimization (Powell, 1973). BFGS is a quasi-Newton method approach. The Hessian matrix (the matrix of the second-order partial derivatives of a constrained function) is estimated to inform the direction of optimization. This requires gradient information (Dennis Jr. & Schnabel, 1983). Finally, SPG uses a line search algorithm to update the search direction. It projects the solution onto the feasible set at each iteration and is more flexible in terms of adjusting for box constraints (Birgin, Martínez, & Raydan, 2008). All other available optimization methods are variations of these often with a smaller computation load or have little information on their approach. Our dataset is robust to the various optimization methods, which did not produce significant differences.

²⁸ Initially, we utilized the Genoud argument, which enables a two-stage optimization beginning with the GENOUD (Genetic Optimization Using Derivatives) optimization function. This stage uses a derivative-based, quasi-Newton method to solve challenging, non-linear optimization problems (Sekhon & Walter R. Mebane, 1998). After testing, we concluded that our data was linear and simple enough that our models didn't benefit from this approach. As it is computationally demand and time consuming, we instead persuade a single stage optimization.

Figure 2.4: Trends and Differences in FDI Net Inflows Per Capita for Actual and Synthetic Ireland

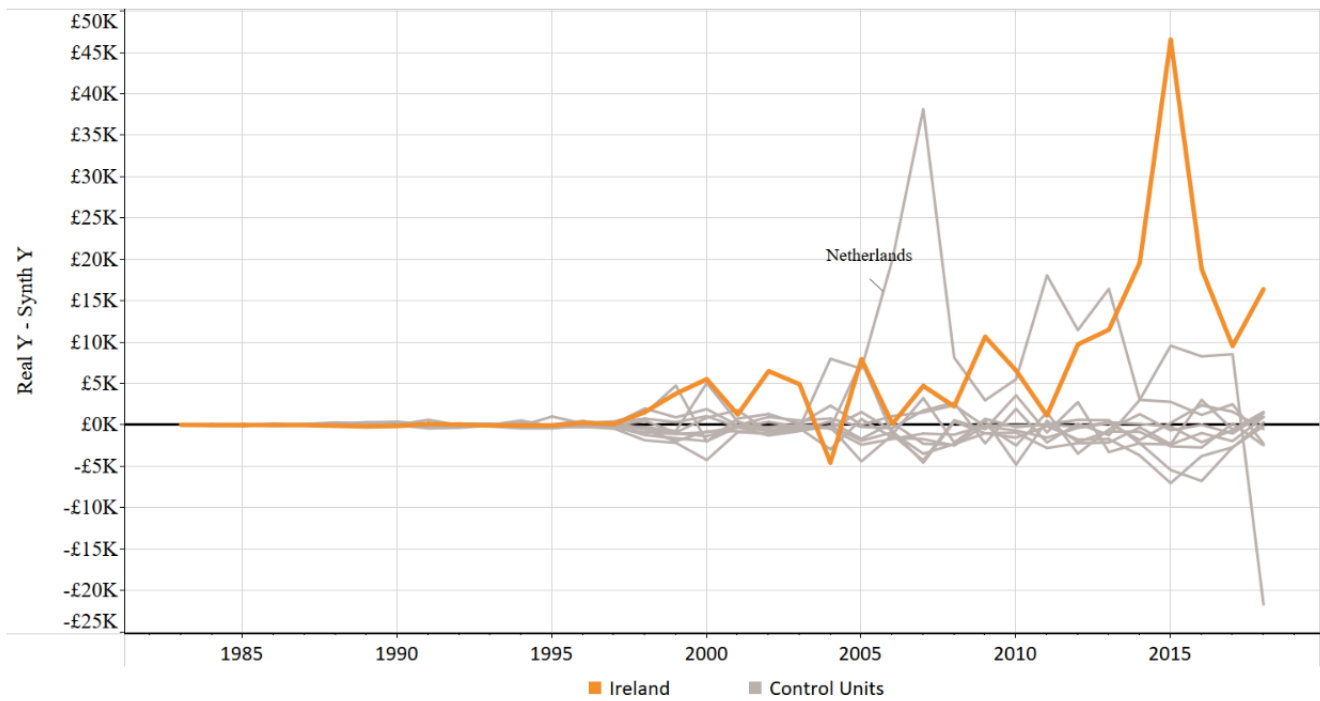


Note: The top panel shows observed (blue) and synthetic (red) FDI net inflows per capita, with the treatment year marking when divergence between the two may emerge. The bottom panel shows the yearly gap between actual and synthetic values, with bars indicating how far actual outcomes are above or below synthetic estimates.

The $MSPE_{pre}$ is 10,456 and $RMSPE_{pre}$ is 102. These values are small, which suggests that the counterfactual is well fitted to Ireland prior to the TCA. Similarly, the placebo tests show that a significant treatment effect occurred. The average $MSPE_{pre}$ for the placebos when performed on the 12 untreated countries is also low with an average $RMSE_{pre}$ of \$244. In all cases, the prediction error is larger than in the primary Irish model. Following the 1997 legislation, all models experience FDI expansion, but none have the same predicted magnitude experienced in Ireland. The Netherlands is the only one to produce similar results with a $RMSPE_{post}$ of 14,276 compared to Ireland's \$14,813. The Netherlands too is regarded as a tax haven and, due to the increasing use of the "Double Dutch" BEPS strategy following 1997, similar results are expected. Aside from the Netherlands, Ireland is a standout amongst the other placebo tests with a $RMSPE$ ratio of 144 as compared to an average of 18 across all others. [See Figure 2.5.] Placebo-in-time tests using earlier intervention dates (1991 and 1994) further support the robustness of the 1997 results. In these alternative specifications, both the real and synthetic series remain largely flat, with near-zero predicted inflows in the counterfactual, indicating no artificial

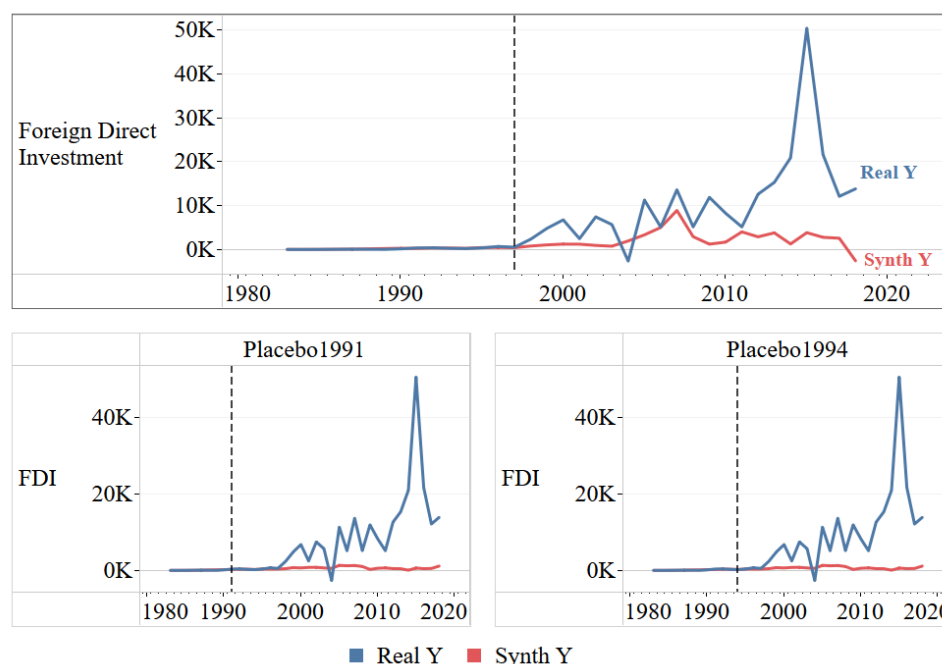
treatment effect prior to the reform. The sharp post-1997 divergence between the actual and synthetic values therefore appears specific to that period, consistent with a structural change coinciding with the tax reduction. [See Figure 2.6.]

Figure 2.5: SCM Placebo Test for FDI Net Inflows per Capita in Ireland vs Donor Countries, 1983–2017



Note: The orange line shows Ireland's gap between actual and synthetic FDI over time. The gray lines represent placebo countries, which received the treatment assignment hypothetically, allowing for comparison of Ireland's deviation relative to the donor pool. Placebo lines provide a reference distribution to assess the distinctiveness of Ireland's trajectory.

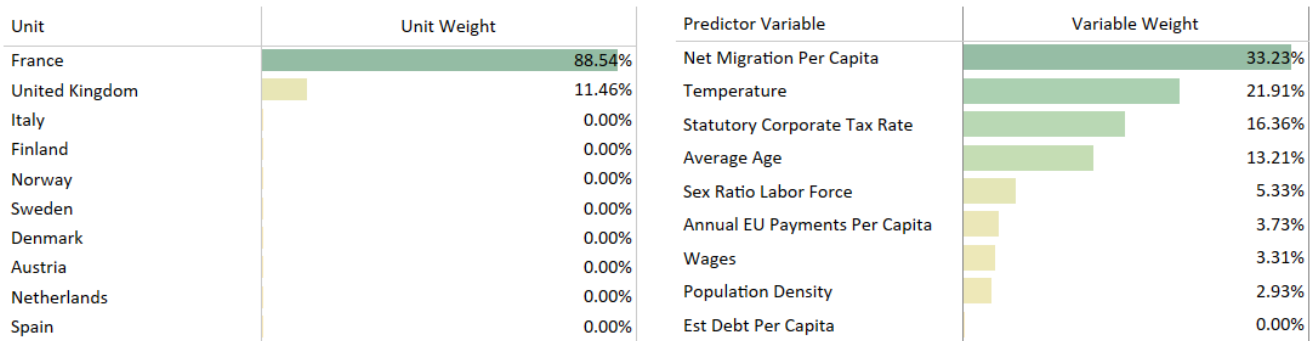
Figure 2.6: Placebo-in-Time Synthetic Control Tests for FDI Net Inflows per Capita, 1983–2017



Note: Each panel compares actual (Real Y, blue) and synthetic (Synth Y, red) FDI inflows per capita for Ireland under different assumed intervention years. The top panel shows the 1997 corporate tax reform, while the lower two panels present placebo interventions in 1991 and 1994. The vertical dashed line marks the specified intervention year.

Figure 2.7 summarises the weights vector W generated for each country in the donor pool to estimate a synthetic Ireland based on pre-trend characteristics. Additionally, the figure shows the weights applied to each variable in V . For FDI, France dominated the model with the United Kingdom also bearing some weight. France's FDI per capita is akin to Ireland's - both in magnitude and in correlations in the pre-treatment period. Ireland averaged \$151 each year, and France averaged \$129 making it the second closest to Ireland next to Denmark. The Pearson correlations are also the second closest at 0.90 next to Austria. However, the figure illustrates net migration, weather, the pre-treatment statutory rate, and the population age are among the seven other characteristics that help minimise the $MSPE_{pre}$.

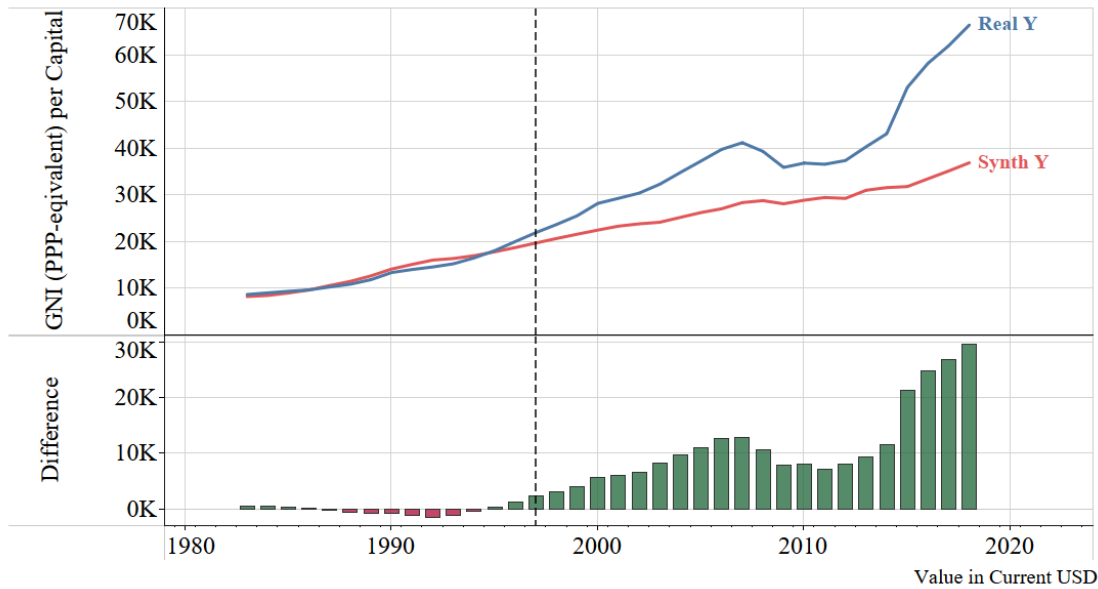
Figure 2.7: Unit and Covariate Weights used to Generate Synthetic Ireland for the FDI Net Income Per Capita Model



Note: The left panel displays the weight assigned to each donor country in constructing synthetic Ireland. The right panel displays weights assigned to covariates, showing their relative contribution to the fit.

Figure 2.8 illustrates that the relationship between the TCA and GNI PPP Per Capita is also positive and resulted in significant income growth between 1998 and 2018. However, as mentioned previously, more tangible results can be obtained by limiting the analysis of the treatment effect to the 1998 – 2014 period, as modified $\widehat{GNI}$ diverges from the GNI in 2015. Even greater constraint on the timeframe to 1998 – 2009 ensures that the $\widehat{GNI}$ and GNI move in near parity (with a $corr_p$ of 99.8%) and have very similar magnitudes with an average annual difference of only 3.1%. By limiting our scope, we ensure that undue influence of non-economic generating BEPS strategies is minimised. The MSPE and RMSPE associated with the pre-intervention and these various post-intervention timeframes is summarised in Table 2.5 in the appendix. In all cases, the pre-intervention period is low relative to the post-intervention values, and Ireland diverges significantly from the counterfactual following the 1997 tax reductions. The treatment effect implies that GNI PPP per capita increased by an estimated \$7,392 by 2009 and \$11,170 by 2014.

Figure 2.8: Trends and Differences in GNI PPP-equivalent per Capita for Actual and Synthetic Ireland

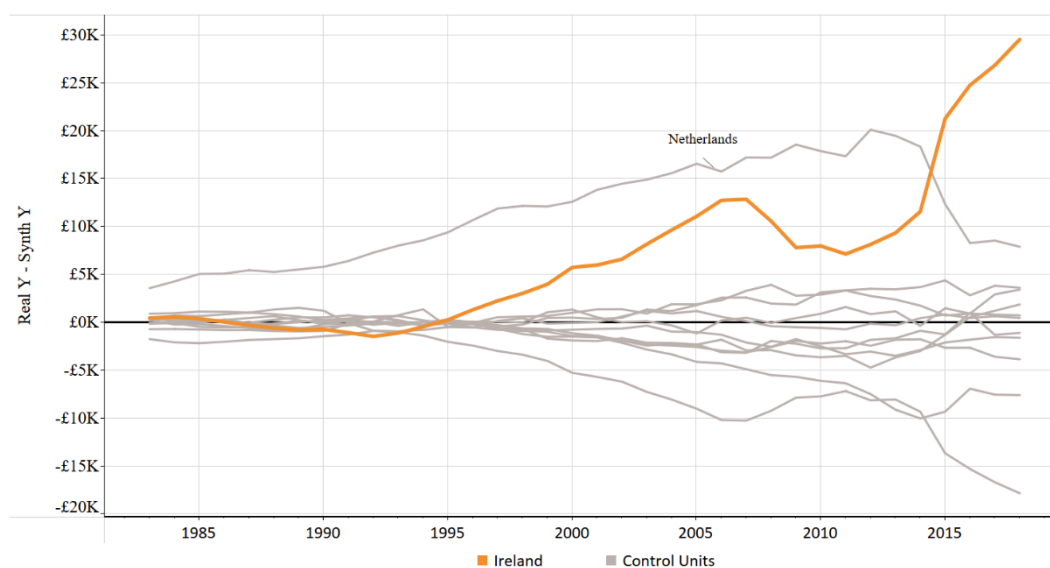


Note: The top panel plots observed (blue) and synthetic (red) GNI PPP per capita, highlighting their relative trajectories before and after the treatment year. The bottom panel displays the annual difference between actual and synthetic values, illustrating the magnitude and direction of the gap over time.

When these model results are contrasted against the placebo tests, Ireland's model exhibits the lowest pre-intervention $MSPE_{pre}$ and the largest post-intervention MSPE, yielding a markedly higher ratio than any other country. Although Norway also shows a post-treatment rise in FDI relative to its synthetic control, its higher $MSPE_{pre}$ suggests a less reliable pre-fit. [See Figure 2.9.] This pattern indicates that the estimated treatment effect for Ireland is statistically distinct from what would be expected under random assignment within the donor pool.

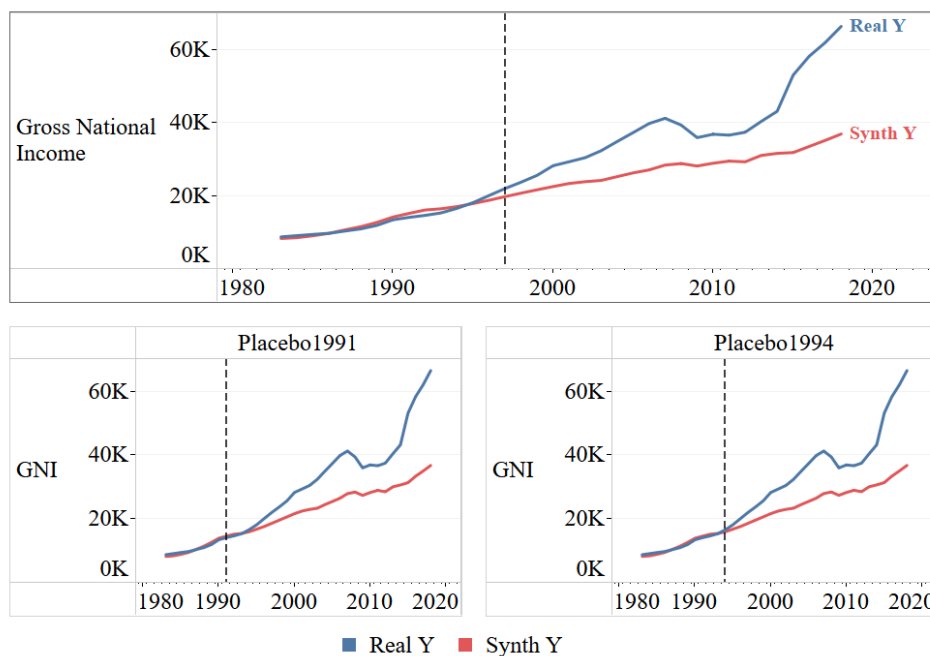
Placebo-in-time tests reinforce this interpretation. When the intervention year is reassigned to 1991 or 1994, the synthetic trajectory closely tracks Ireland's actual FDI path, maintaining a nearly linear trend through the mid-1990s. Divergence emerges only after 1997, at which point actual inflows accelerate sharply while the synthetic series continues along its pre-existing slope. [See Figure 2.10.] This stability across placebo years implies that the post-1997 deviation reflects a structural shift unique to that period rather than a continuation of earlier dynamics.

Figure 2.9: GNI PPP Per Capita Gap in Ireland vs Other Country Placebos



Note: The orange line shows Ireland's gap between actual and GNI PPP-equivalent per Capita over time. The gray lines represent placebo countries, which received the treatment assignment hypothetically, allowing for comparison of Ireland's deviation relative to the donor pool. Placebo lines provide a reference distribution to assess the distinctiveness of Ireland's trajectory.

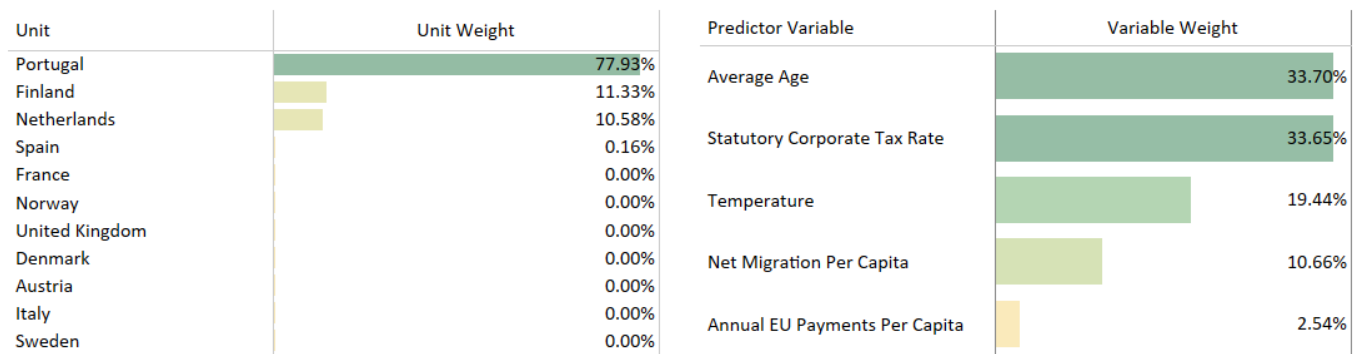
Figure 2.10: Placebo-in-Time Synthetic Control Tests for GNI (PPP-equivalent) per Capita, 1983–2017



Note: Each panel compares actual (Real Y in blue) and synthetic (Synth Y in red) GNI (PPP-equivalent) per capita for Ireland under different assumed intervention years. The top panel shows the 1997 corporate tax reform, while the lower two panels present placebo interventions in 1991 and 1994. The vertical dashed line marks the specified intervention year.

Figure 2.11 shows the weights applied for both W and V . A weighted combination of Portugal, Finland, and the Netherlands are applied. All other countries receive a zero weight in the vector. The variables that help define the untreated units' associated characteristics are average age, the prior tax rate, the temperature, and net migration per capita. All other variables received little or no weight. The presence of the statutory rate seems mostly influenced by the late-1980s, as Portugal had also made significant cuts to the 40% level around the same time as Ireland, but had not followed Ireland's trend throughout the 1990s.

Figure 2.11: Unit and Variable Weights used to Generate Synthetic Ireland for the GNI PPP Per Capita Model



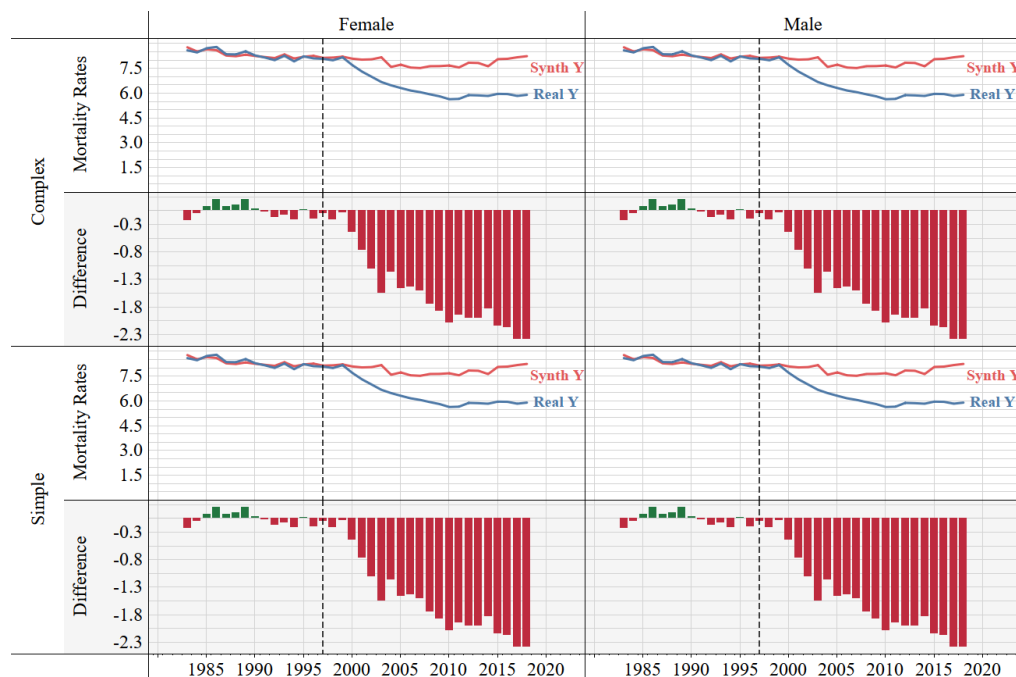
Note: The left panel shows country weights used to construct synthetic Ireland, while the right shows covariate weights.

Our results also suggest that mortality rates declined significantly as a result of the Tax Consolidation Act in Ireland. [See Figure 2.12 below.] These results are summarised by female and male populations and contain both the simple and complex models. Across all models, divergence from pre-intervention levels doesn't commence immediately after the policy change but rather near 1999. This could be due to lag effects, the gradually increasing rate reductions, or other factors that are excluded from the model. Lag effects are expected, as mortality rate changes are unresponsive in the short-run. They result from economic growth, consumption and behavioral changes at the household level, and migration, amongst others. These changes take time.

The female model results differ from the male model results in that the incorporation of risk factors greatly decreases the female MSPE in the pre-intervention period, while it increases the error from males. This implies that the donor pool weighting can synthesise Ireland better through the inclusion of health risk factors for females.

For males, the inclusion of the additional variables better informs the model but weighting and minimization become more complex. Weights change and thus the error also increases. While further research is warranted, the conclusions are consistent across all models; devoid of the TCA, mortality rates would have improved and remained relatively low. However, the resulting benefits of the TCA yielded an improvement in mortality rates estimated to be between 25% and 31% for females and 28% and 39% for men by 2007. By 2018, the improve gap is estimated to be between 46% and 53% for females and 34% and 40% for men by 2018. See Table 2.6 for a summary of the MSPE and RMPE for both the pre- and post-intervention periods.

Figure 2.12: Trends and Differences in Male and Female Mortality Rates for Actual and Synthetic Ireland



Note: The top panels display observed (blue) and synthetic (red) mortality rates for males and females, across both simple and complex model specifications. The bottom panels show the annual differences between the two series, with bars indicating the gap between Real Y and Synth Y for each year. Simple models exclude risk factors, while complex models incorporate them as covariates, allowing direct visual comparison across sex and model type.

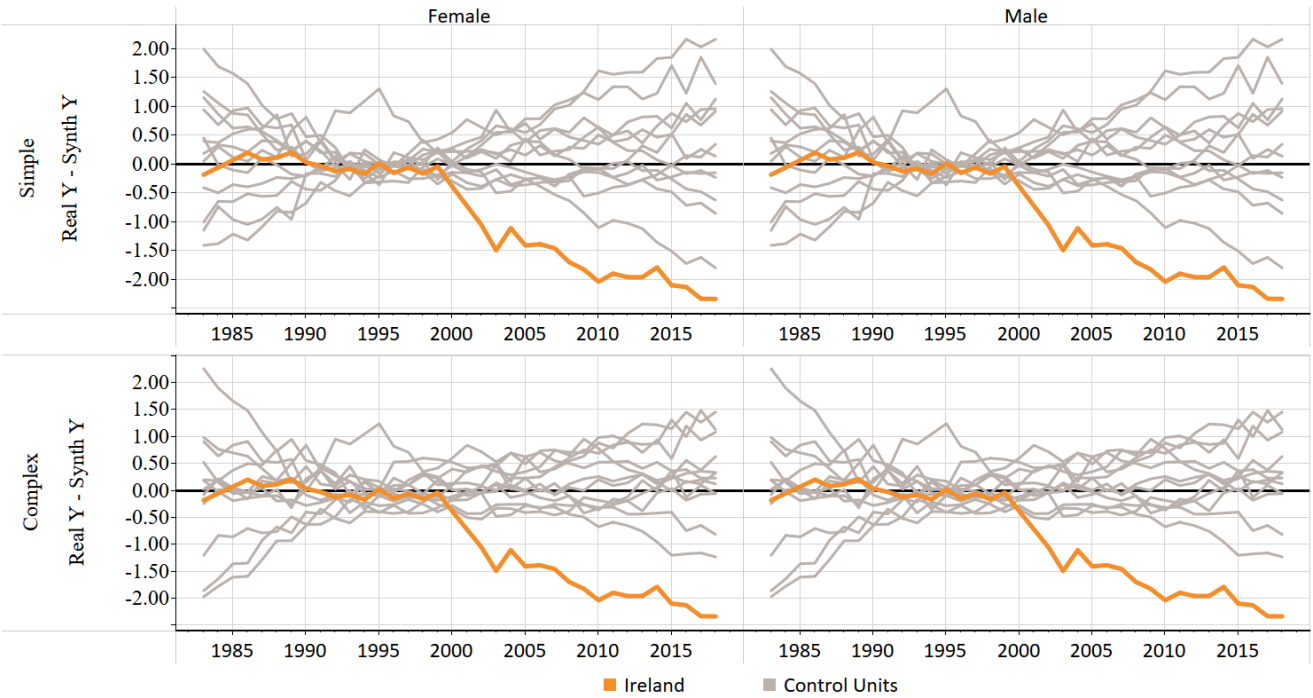
The placebo tests, shown in Figure 2.13, produced informative results. In all cases, the Fisher's exact p -value of the mortality models is roughly comparable to those of the FDI per capita and GNI PPP per capita models, at approximately 0.077. The Irish model has the smallest or near-smallest gap during the pre-treatment period and the largest by 2018. However, the placebo models, unlike in the FDI and GNI cases, display considerable

variability in pre-treatment fit and in several instances exhibit narrowing rather than widening gaps post-treatment. As many of the high pre-treatment gap countries also show large post-treatment deviations, this pattern may reflect greater noise in health-related outcomes and potentially slower adjustment processes.

Placebo-in-time tests provide further context. When the intervention year is reassigned to earlier dates, the synthetic and actual mortality trajectories for Ireland remain closely aligned, with little sign of divergence until roughly 1999. This persistence suggests that the observed post-1997 mortality decline emerged only gradually, consistent with a lagged response to structural or policy-related changes rather than an immediate contemporaneous effect. [See Figure 2.14.]

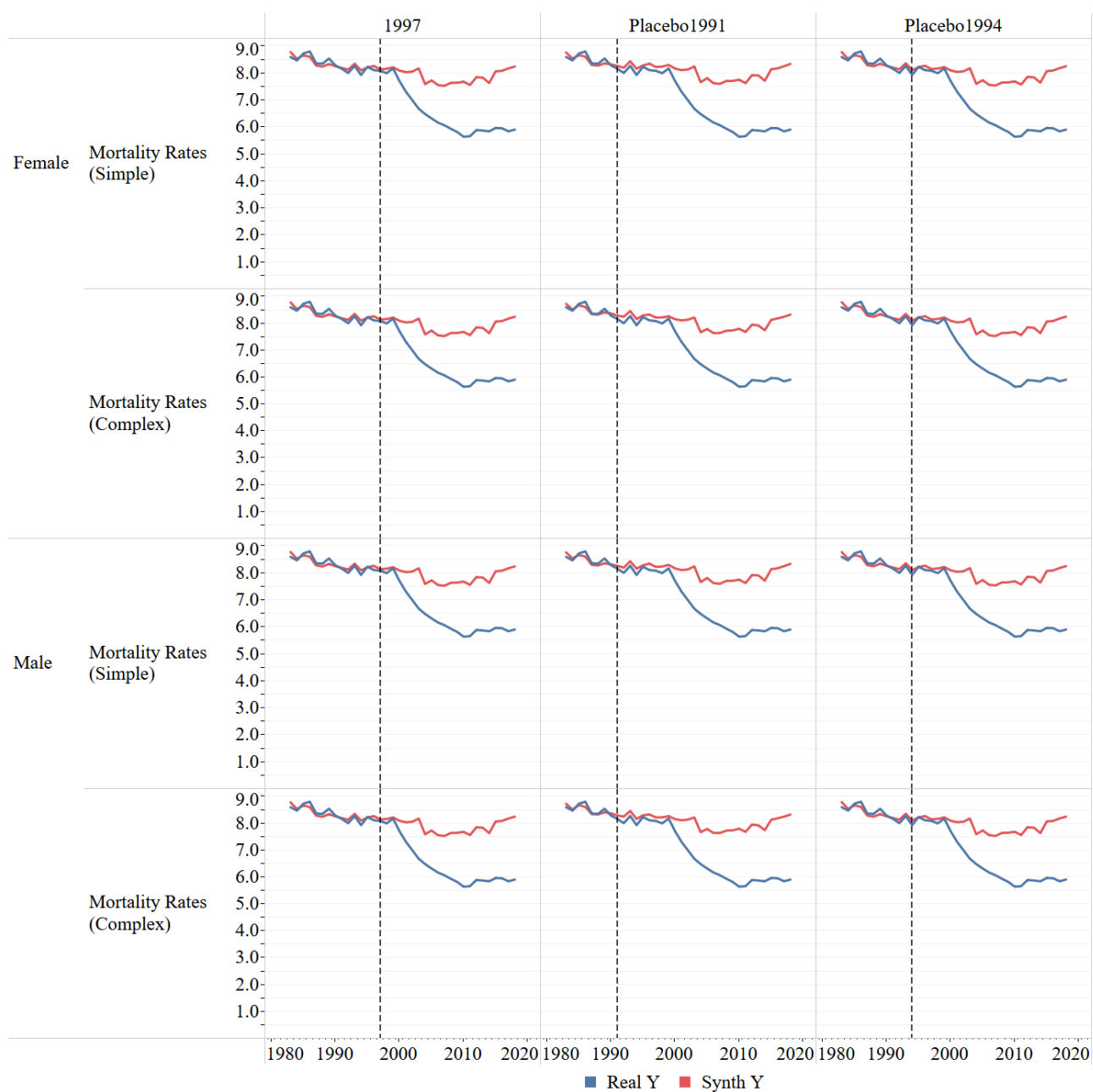
Figure 15 in the Appendix presents the pruned placebo results, which exclude donor countries with poor pre-intervention fit. Pruning removes countries whose pre-treatment MSPE exceeds a reasonable threshold, ensuring that comparisons are made only among well-fitted counterfactuals. After pruning, only a limited number of countries remain, with none retained in the female-simple specification. Among the remaining cases, Ireland continues to exhibit the lowest $MSPE_{Pre}$ and the largest post-treatment effect following the TSA, reinforcing the robustness of the main findings.

Figure 2.13: Age-adjusted Mortality Rate Gap in Ireland vs Other Country Placebos for Males and Females



Note: Each quadrant corresponds to a combination of sex (male/female) and model specification (simple/complex). Orange lines show Ireland, while gray lines show placebo countries. Simple models exclude risk factors; complex models include them.

Figure 2.14: Placebo-in-Time Synthetic Control Tests for Mortality Rate Models, 1983-2017



The unit weight vector W contains five non-zero countries. The same few countries appear in all mortality models, and they are reflective of those in the W from other Y s. They include the Netherlands, Portugal, Spain, Austria and Finland. Without risk factors included, temperature and age are largely weighted variables to minimise the $MSPE_{pre}$. In the complex model, risk factors too are weighted heavily. [See Figure 2.15 and Figure 2.16.]

Figure 2.15: Unit and Variable Weights used to Generate Synthetic Ireland for the Simple Mortality Rate Model

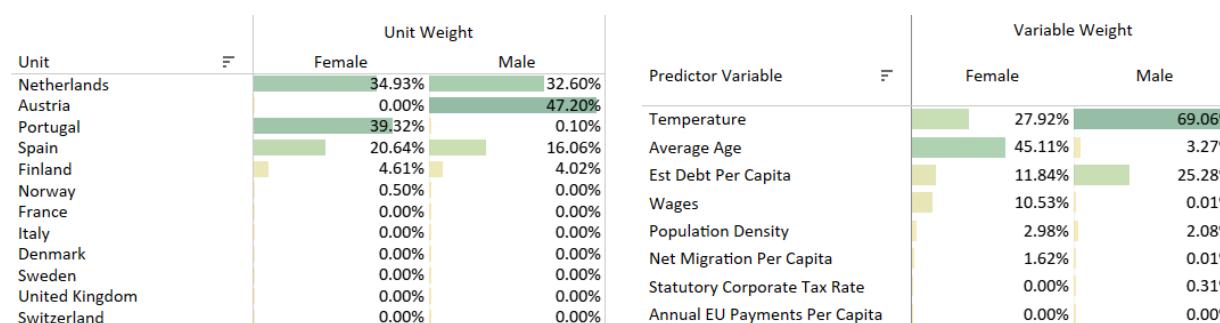
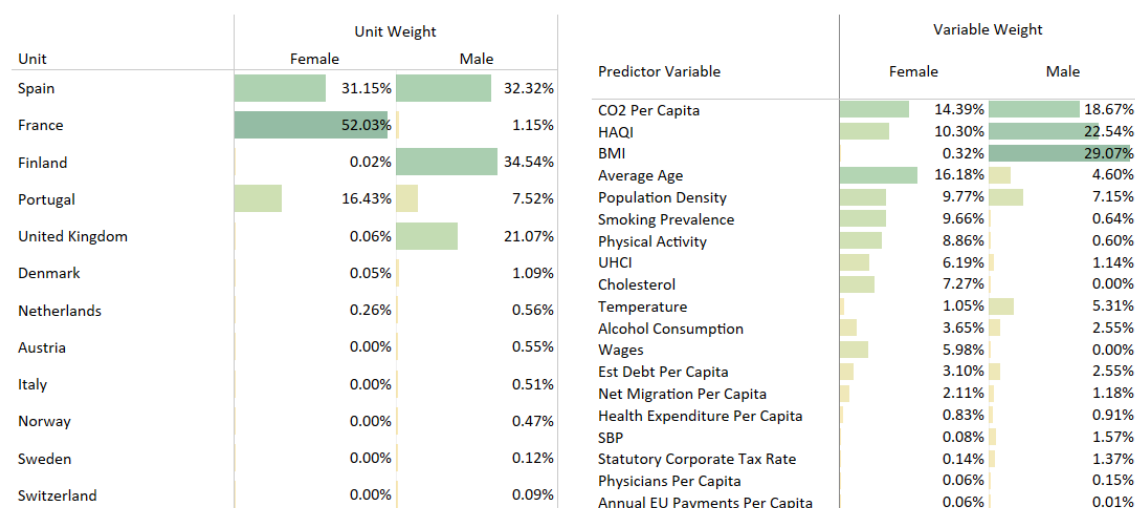


Figure 2.16: Unit and Variable Weights used to Generate Synthetic Ireland for the Complex Mortality Rate Model



7 Conclusion and Implications

Ireland's experience represents a prominent case of large-scale corporate tax undercutting within developed economies. The results indicate that this strategy is associated with a sustained divergence in economic outcomes, with Ireland outperforming comparable countries in terms of capital inflows and income. These findings are consistent with the view that persistent tax differentials can influence the allocation of multinational investment, particularly when combined with favorable institutional and macroeconomic conditions.

The implications for broader welfare outcomes are less direct. Although improvements in population health are observed alongside Ireland's economic expansion, these effects are gradual and exhibit greater variability. This pattern is consistent with a framework in which fiscal policy affects welfare through indirect

channels such as income, employment, and public expenditure, and is mediated by structural and behavioral factors. The estimates should therefore be interpreted as reflecting relative divergence under identifying assumptions, rather than the causal impact of a single policy, and may represent an upper bound in the presence of spillovers or general equilibrium effects.

These findings also have implications for how evidence from tax policy is interpreted more generally. In settings where policy changes coincide with broader structural transformations, estimated effects are likely to capture the joint influence of multiple factors rather than a single intervention. The concentration of weights within the donor pool further reinforces the importance of interpreting results as comparative benchmarks rather than precise causal estimates. This underscores the need for caution when generalizing from individual country experiences, particularly in highly open economies.

More broadly, the analysis highlights the importance of evaluating tax policy within a wider structural and international context. The period under study coincides with multiple concurrent developments, including European integration, human capital accumulation, and changes in global production networks. Within this setting, counterfactual methods provide a useful framework for assessing how economic and population-level outcomes evolve jointly, even when causal mechanisms cannot be fully isolated. From a policy perspective, Ireland's case illustrates both the effectiveness and the constraints of tax competition in an increasingly coordinated international environment.

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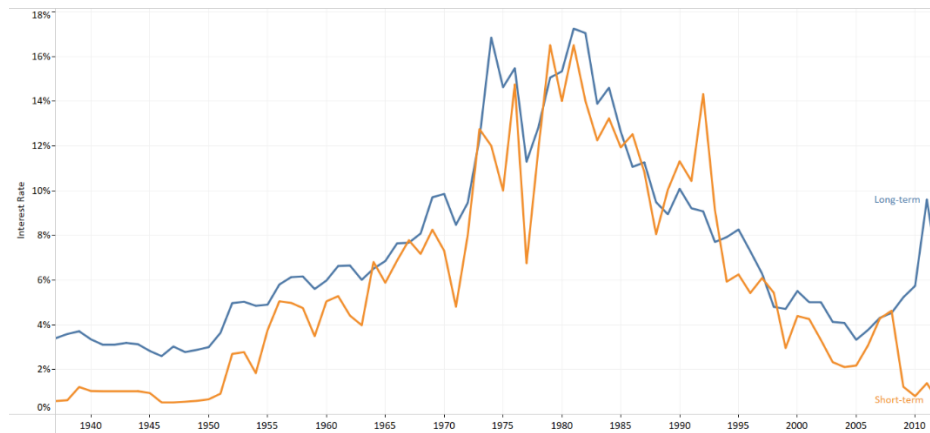
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Appendix

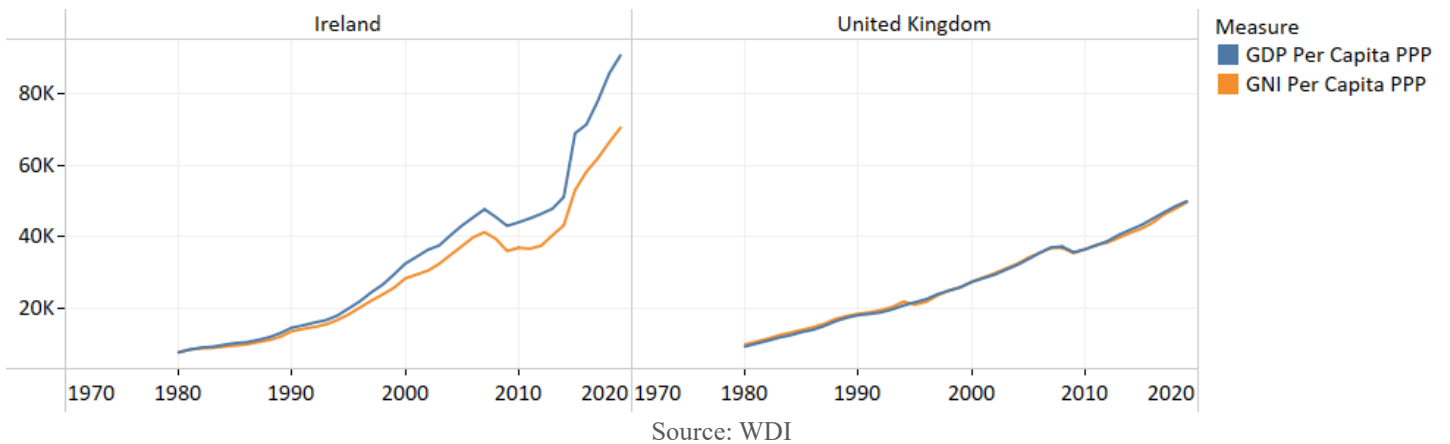
Figure 2.17: Long-term and Short-term Interest Rate Estimates in Ireland, 1937 – 2012



Source: Gerlach & Steward, 2014

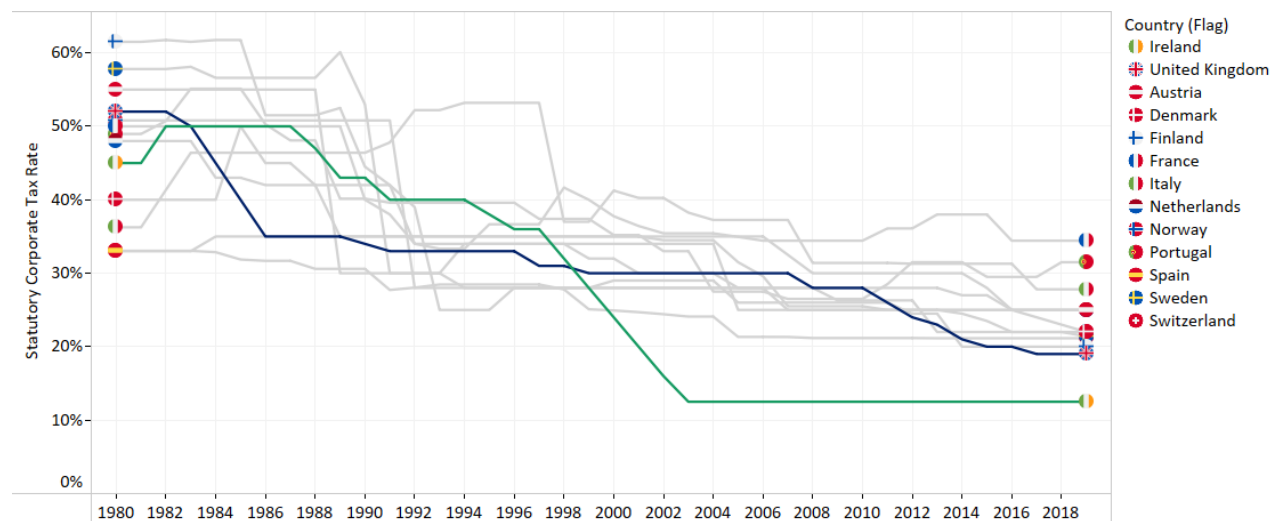
Note: The blue line shows long-term interest rates, and the orange line shows short-term interest rates over time.

Figure 2.18: Gross Domestic Product (GDP) vs Gross National Income (GNI) in Ireland and the UK, 1970 – 2019



Note: The orange line represents GNI PPP per capita and the blue line represents GDP PPP per capita. Charts are shown separately for Ireland (left) and the UK (right) to allow direct visual comparison.

Figure 2.19: Statutory Corporate Tax Rates by Country, 1980 – 2019



Source: Tax Foundation

Note: The lines depict statutory corporate tax rates (percent) for Western European countries. All countries are shown in gray, with the UK highlighted in blue and Ireland in green.

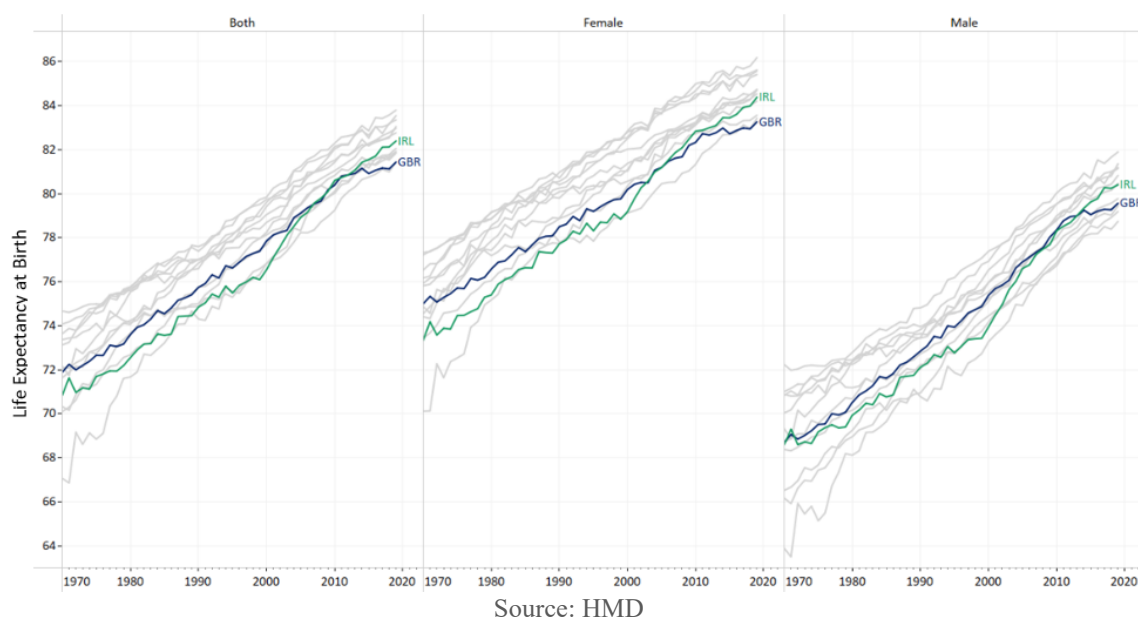
Figure 2.20: Age-adjusted Mortality Rates by Sex by Country, 1970 - 2019



Source: HMD

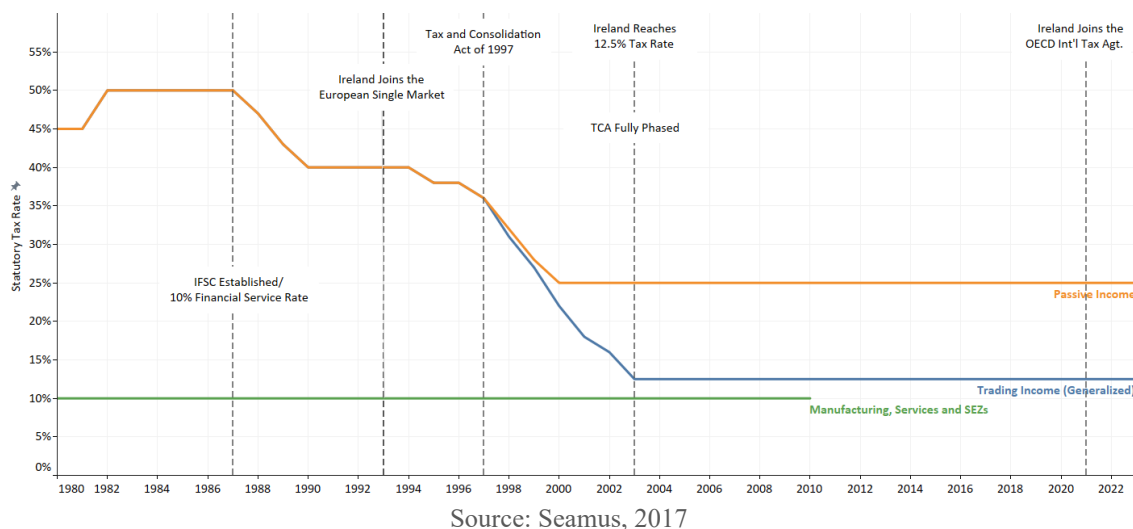
Note: The lines show age-adjusted mortality rates for each country, with Ireland (green) and the UK (blue) highlighted. Male, female, and combined series are presented separately. Y-axes do not start at zero.

Figure 2.21: Life Expectancy at Birth (LEB) by Sex and Country, 1970 - 2019



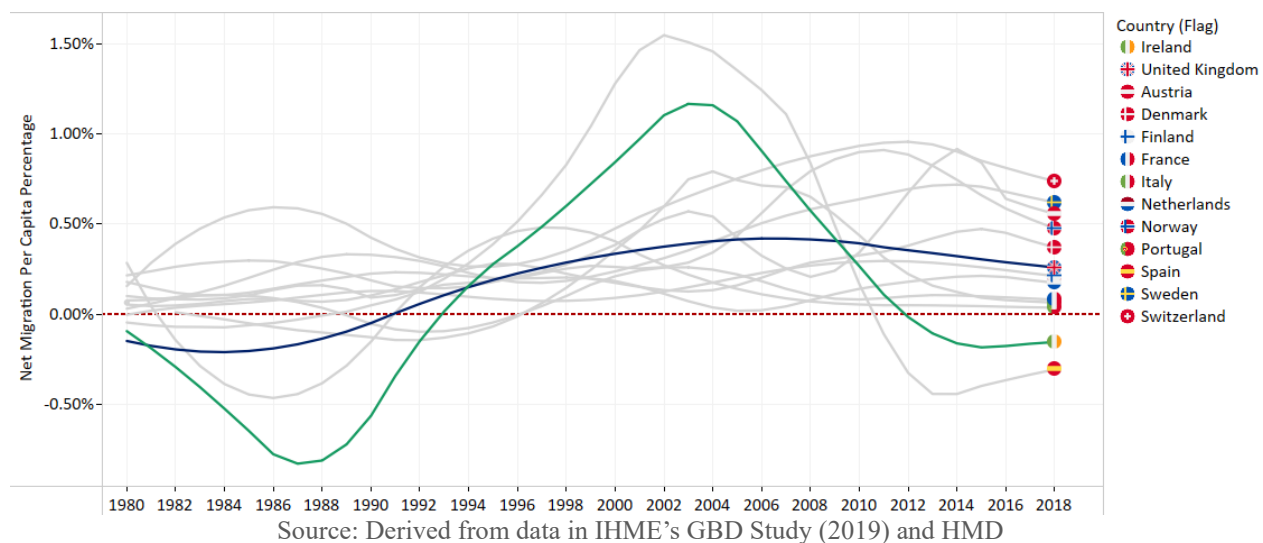
Note: The panels show average life expectancy at birth over time for male and female populations. Ireland is in green, the UK in blue, and other countries in gray. Y-axes do not start at zero.

Figure 2.22: Detailed Corporate Tax Break-down and Timeline for Ireland, 1980 - 2019



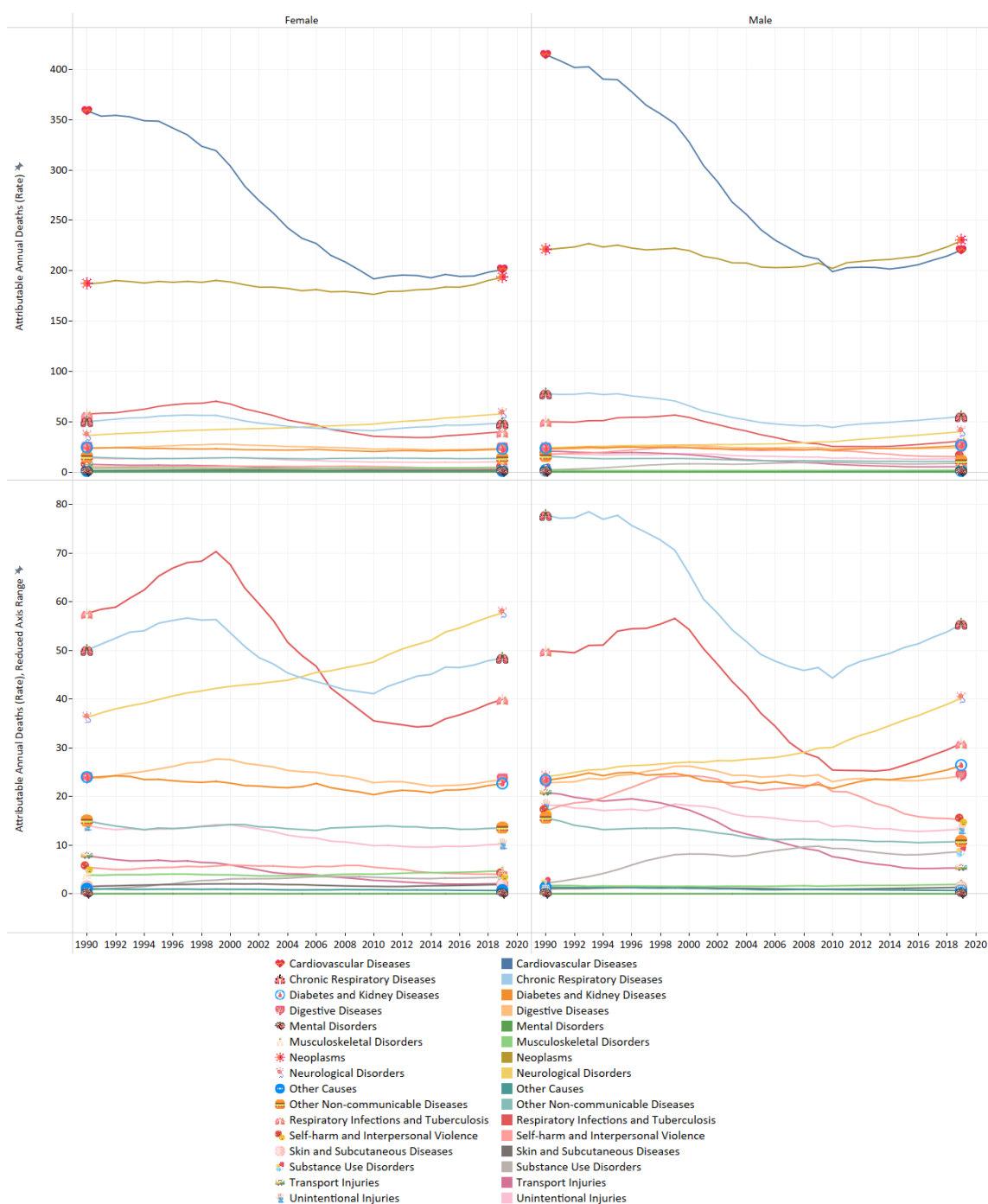
Note: The chart shows statutory tax rates for passive income (orange), trading income (blue), and manufacturing/SEZ rates (green). Reference lines mark key policy changes, including the 1997 TCA.

Figure 2.23: Net Migration per Capita by Country, 1980 - 2018



Note: Lines show net migration per capita over time for several Western European countries. Ireland is highlighted in green and the UK in blue; all other countries appear in gray. Positive values indicate net migration-in.

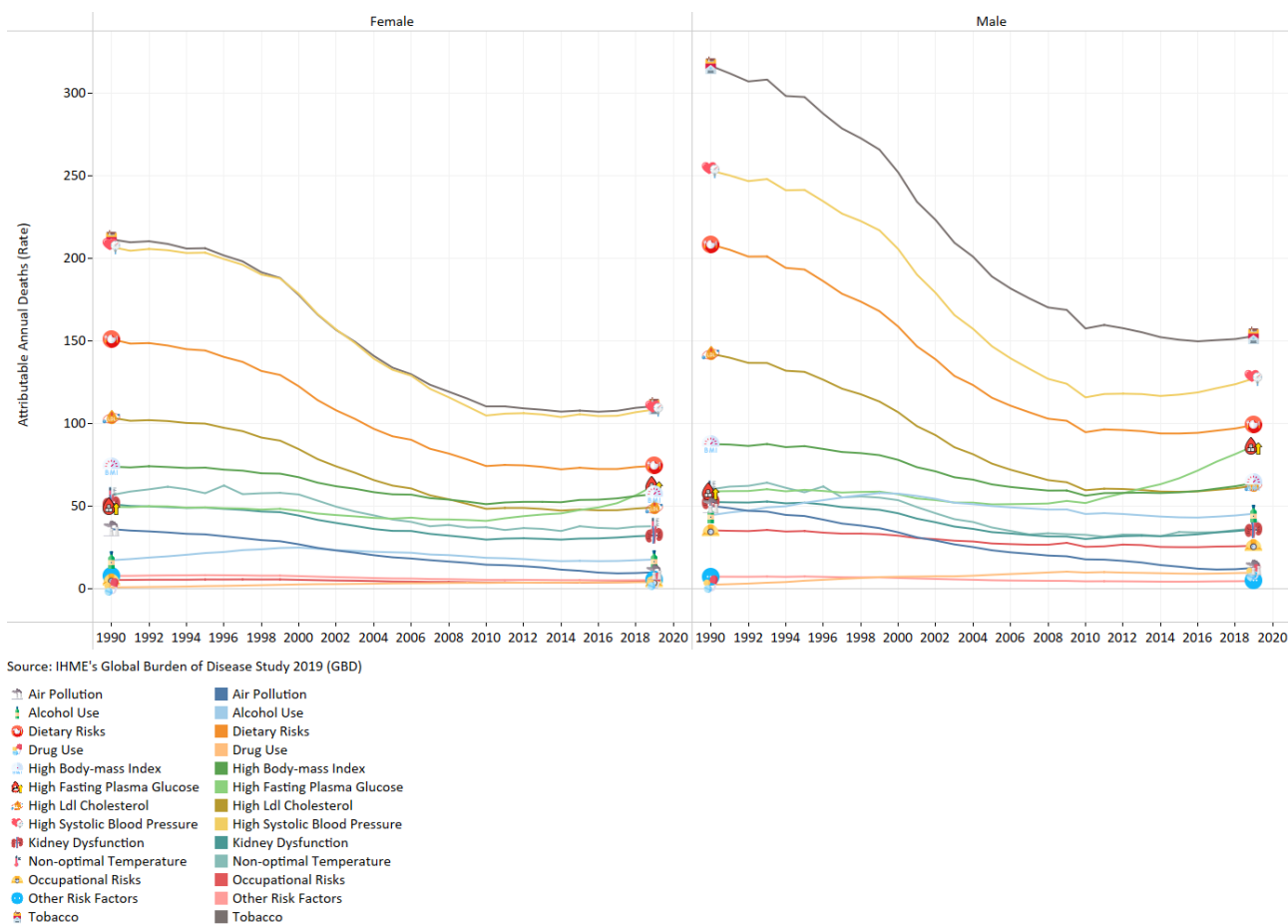
Figure 2.24: Deaths (Rate) by Cause in the Ireland, 1990 - 2019



Source: IHME's GBD Study (2019)

Note: Lines show attributable death rates by cause for males and females. The top row shows the full scale, dominated by cardiovascular and neoplasm deaths; the bottom row uses a reduced axis range to show smaller causes. Rates are per 100,000 population, with cardiovascular disease averaging roughly 250 per 100,000.

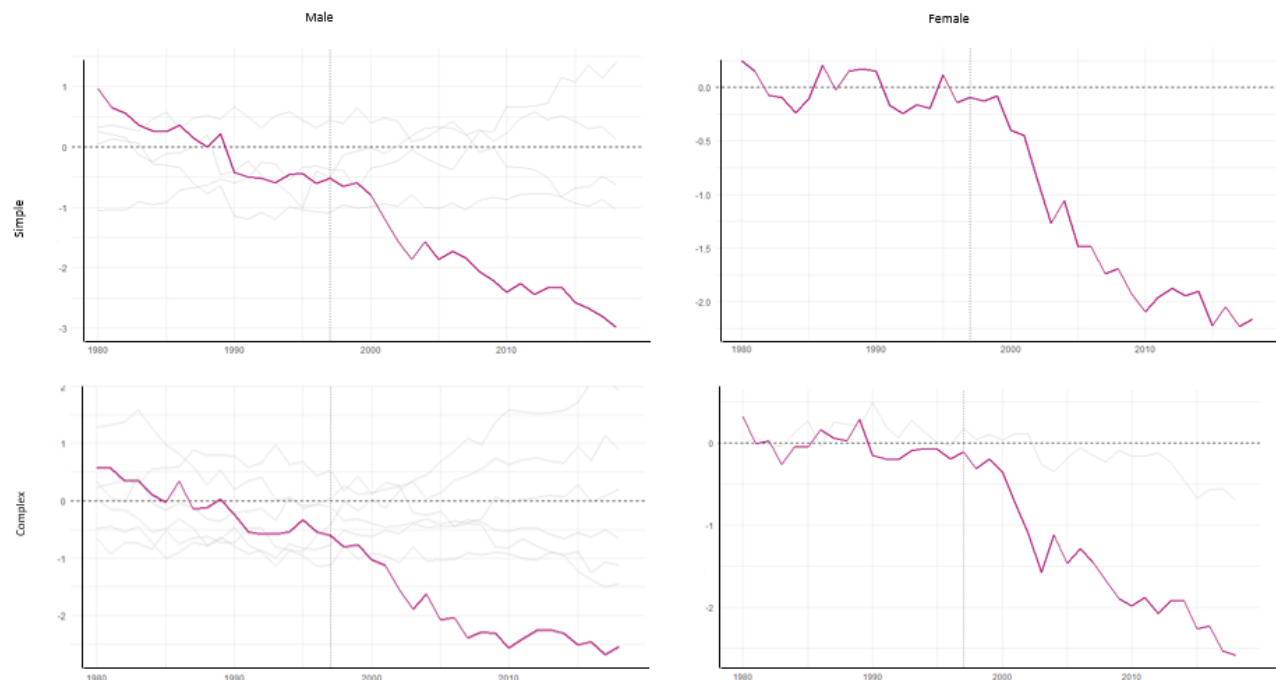
Figure 2.25: Deaths (Rate) by Risk Factor in the Ireland, 1990 - 2019



Source: IHME's GBD Study (2019)

Note: Lines and icons show attributable death rates by risk factor for females (left) and males (right). Rates are per 100,000 population.

Figure 2.26: Pruned Age-adjusted Mortality Rate Gap in Ireland vs Other Country Placebos for Males and Females



Note: Panels show the gap between actual and synthetic mortality rates for males and females under simple and complex model specifications. Ireland is shown in red and placebo countries in gray. The donor pool has been pruned, which is a process of removing donor units with poor pre-treatment fit to better visualize Ireland's relative deviation.

Table 2.1: Description of Measures used in Models

Measure	Measure Description	Available by Sex	Year Range	Year Range Continuous	Derived Measure	Measure Source
Alcohol Consumption	Alcohol consumption, age standardized, in grams per day	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Annual EU Payments Per Capita	Annual EU expenditure data (in current prices) for specific EU funds paid - ERDF, Cohesion Fund, EAFRD/EAGGF and ESF per capita	No	1987-2018	No	Yes	Cohesion Fund Data
Average Age	Average age of population	Yes	1980-2019	Yes	Yes	Human Mortality Database
Average Temperature	Mean temperature annually	No	1980-2019	Yes	No	Global Burden of Disease 2019 Study
BMI	Mean BMI	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Central Bank Debt Per Capita	Central bank debt per capita	No	1980-2019	No	Yes	International Monetary Fund Datamapper
Cholesterol	Cholesterol (total, mean per capita)	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
CO2 Emissions Per Capita	CO2 emissions annually per capita	No	1980-2019	Yes	No	Global Carbon Project 2019
Exports Per Capita	Net exports of goods and services per capita	No	1980-2019	Yes	Yes	World Bank World Development Indicators
FDI Net Inflows Per Capita	Foreign direct investment net inflows per capita	No	1980-2019	No	Yes	World Bank World Development Indicators
GNI Per Capita PPP	Gross national income per capita in current US dollars adjusted for PPP	No	1980-2019	Yes	Yes	World Bank World Development Indicators
HAQI	Healthcare access and quality index	No	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Health Expenditure Per Capita	Total national health expenditure per capita	No	1980-2019	No	No	OECD Health Data
Mortality Rate, Age-adjusted	Age-adjusted mortality rates	Yes	1980-2019	Yes	Yes	Human Mortality Database
Net Migration Per Capita	UN's net migration estimates per 1000	No	1980-2018	Yes	No	Global Burden of Disease 2019 Study
Physical Activity	Total physical activity (met-min/week), age-standardized	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Population Density	Population per square kilometer of land area	No	1980-2019	Yes	No	World Bank World Development Indicators
SBP (Blood Pressure)	Mean systolic blood pressure (mmHg)	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Sex Ratio Labor Force	Ratio of female to male labor force participation	No	1990-2019	Yes	No	World Bank World Development Indicators
Smoking Prevalence	Age-standardized smoking prevalence	Yes	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Statutory Corporate Tax Rate	Historical "headline" corporate tax rate	No	1980-2019	Yes	No	Tax Foundation
UHCI	Universal health coverage index	No	1980-2019	Yes	No	Global Burden of Disease 2019 Study
Unemployment Rate	Harmonized unemployment rate	Yes	1983-2019	No	No	OECD Labor Force Data
Wages	Estimated average wages	No	1980-2019	No	No	Mitchell's International Historical Statistics and OECD Forecast

Table 2.2: Summary Statistics for Measures used in Models

Measure	Average	Median	Minimum	Maximum	Percentile (25)	Percentile (75)	Standard Deviation	Variance
Alcohol Consumption	15.7571	15.7291	6.5703	27.2186	12.8188	19.3290	4.3984	19.3458
Annual EU Payments Per Capita	51.1831	22.0777	0.0000	544.0864	0.0000	65.9556	77.6884	6,035.4892
Average Age	37.5180	37.6639	30.0761	46.3755	35.4008	39.7168	3.0727	9.4416
Average Temperature	9.6997	9.3886	1.5448	16.5169	7.2647	12.2790	3.5220	12.4048
BMI	25.4225	25.3772	23.5863	27.4915	24.8322	25.9948	0.7863	0.6182
Central Bank Debt Per Capita	13,412.9418	11,067.8205	88.4801	63,850.7362	3,587.9741	20,952.7844	11,734.7929	137,705,364.7328
Cholesterol	3.4765	3.4745	3.0874	3.8814	3.3502	3.6097	0.1782	0.0318
CO2 Emissions Per Capita	8.0141	7.7875	1.7550	14.2440	6.3310	9.7900	2.3409	5.4800
Exports Per Capita	12,163.4268	7,487.7158	147.8269	104,064.3042	2,838.6999	15,208.3346	14,144.7480	200,073,895.8974
FDI Net Inflows Per Capita	1,279.4172	230.1840	-19,985.0788	50,417.3528	34.4573	932.4463	4,260.7100	18,153,649.9719
GNI Per Capita PPP	30,655.5735	28,835.0582	5,936.3071	71,766.2357	18,171.8808	41,073.4710	15,102.9549	228,099,246.8207
HAQI	85.9932	86.8506	59.7385	96.7775	80.5292	92.3430	7.5897	57.6033
Health Expenditure Per Capita	2,348.5700	2,024.4195	158.0570	6,942.4100	1,002.8318	3,442.4963	1,582.5146	2,504,352.3479
Mortality Rate, Age-adjusted	8.8737	8.7645	5.4557	13.0689	8.0626	9.6536	1.2198	1.4879
Net Migration Per Capita	2.2996	1.8450	-22.0410	22.6810	0.5650	3.8770	3.6086	13.0222
Physical Activity	3,531.2142	3,510.8163	2,390.2830	5,331.5969	3,060.4572	3,985.8509	617.4116	381,197.1304
Population Density	131.3219	105.7008	10.6114	515.1433	50.5995	186.1596	116.2078	13,504.2498
SBP (Blood Pressure)	130.2062	130.4352	117.6400	144.2913	127.6768	132.5431	4.0030	16.0240
Sex Ratio Labor Force	0.7778	0.8066	0.4940	0.9406	0.7191	0.8476	0.0964	0.0093
Smoking Prevalence	0.2857	0.2835	0.1265	0.5547	0.2343	0.3332	0.0713	0.0051
Statutory Corporate Tax Rate	0.3387	0.3225	0.1250	0.6175	0.2650	0.3960	0.1064	0.0113
UHCI	86.0528	87.2391	63.3998	96.7060	79.8114	92.7085	7.5962	57.7022
Unemployment Rate	0.0837	0.0743	0.0154	0.2888	0.0516	0.1005	0.0440	0.0019
Wages	35,701.1748	38,804.7900	1,714.0500	68,121.6100	25,075.4300	47,318.5300	16,226.8230	263,309,786.2868

Table 2.3: Countries by Model

Model	Sex	J(n)	c(n)	Countries in J
Foreign Direct Investment	Both	11	10	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Spain, Sweden, United Kingdom
Gross National Income	Both	12	11	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom
Mortality Rates (Simple)	Female	13	12	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom
	Male	13	12	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom
Mortality Rates (Complex)	Female	13	12	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom
	Male	13	12	Ireland, Austria, Denmark, Finland, France, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom

Table 2.4: Independent Variables by Model

Model	Sex	Count of Vars	Independent Vars
Foreign Direct Investment	Both	9	Annual EU Payments Per Capita (B), Average Age (B), Est Debt Per Capita (B), Net Migration Per Capita (B), Population Density (B), Sex Ratio Labor Force (B), Statutory Corporate Tax Rate (B), Temperature (B), Wages (B)
Gross National Income	Both	5	Annual EU Payments Per Capita (B), Average Age (B), Net Migration Per Capita (B), Statutory Corporate Tax Rate (B), Temperature (B),
Mortality Rates (Simple)	Female	9	Annual EU Payments Per Capita (B), Average Age (F), Est Debt Per Capita (B), GNI Per Capita (B), Net Migration Per Capita (B), Population Density (B), Statutory Corporate Tax Rate (B), Temperature (B), Wages (B)
	Male	9	Annual EU Payments Per Capita (B), Average Age (M), Est Debt Per Capita (B), GNI Per Capita (B), Net Migration Per Capita (B), Population Density (B), Statutory Corporate Tax Rate (B), Temperature (B), Wages (B)
Mortality Rates (Complex)	Female	20	Alcohol Consumption (F), Annual EU Payments Per Capita (B), Average Age (F), BMI (F), Cholesterol (F), CO2 Per Capita (B), Est Debt Per Capita (B), GNI Per Capita (B), HAQI (B), Health Expenditure Per Capita (B), Net Migration Per Capita (B), Physical Activity (F), Physicians Per Capita (B), Population Density (B), SBP (F), Smoking Prevalence (B), Statutory Corporate Tax Rate (B), Temperature (B), UHCI (B), Wages (B)
	Male	20	Alcohol Consumption (M), Annual EU Payments Per Capita (B), Average Age (M), BMI (M), Cholesterol (M), CO2 Per Capita (B), Est Debt Per Capita (B), GNI Per Capita (B), HAQI (B), Health Expenditure Per Capita (B), Net Migration Per Capita (B), Physical Activity (M), Physicians Per Capita (B), Population Density (B), SBP (M), Smoking Prevalence (B), Statutory Corporate Tax Rate (B), Temperature (B), UHCI (B), Wages (B)

Table 2.5: Summary of MSPE and RMSPE for the GNI PPP Per Capita Models for Pre- and Various Post-Intervention Timeframes

	$t, \dots, \tau$	τ + 1, ..., 2009	τ + 1, ..., 2014	τ + 1, ..., 2018
$MSPE_{post}$	966,347	71,744,163	72,173,352	172,578,651
$RMSPE_{post}$	983	8,470	8,495	13,137

Table 2.6: Summary of MSPE and RMSPE for the Age-adjusted Mortality Rates by Sex and Model

	Male, Simple	Female Simple	Male, Complex	Female, Complex
$MSPE_{pre}$	0.02676	0.17520	0.23532	0.02622
$MSPE_{post}$	2.65598	4.33680	4.21949	2.88842
$RMSPE_{pre}$	0.16358	0.41857	0.48509	0.16193
$RMSPE_{post}$	1.62972	2.08250	2.05414	1.69954

Note: Rows report pre- and post-treatment MSPE and RMSPE values. Columns correspond to the four combinations of sex (male/female) and model type (simple/complex).

Table 2.7: Fischer's Exact P-value by Target and Placebo Models

	Type	Unit Name	FDI Per Capita	GNI PPP Per Capita	Mortality Rates (Simple)		Mortality Rates (Complex)	
			Both	Both	Female	Male	Female	Male
Fischer's Exact P-value	Treated	Ireland	0.09091	0.08333	0.07692	0.07692	0.07692	0.07692
	Donor	Austria	0.54545	0.83333	1.00000	1.00000	1.00000	0.92308
		Denmark	0.45455	0.75000	0.76923	0.76923	0.53846	0.76923
		Finland	0.81818	0.25000	0.30769	0.23077	0.92308	0.23077
		France	0.36364	0.16667	0.23077	0.30769	0.46154	0.53846
		Italy	1.00000	1.00000	0.69231	0.84615	0.61538	0.15385
		Netherlands	0.18182	0.66667	0.92308	0.69231	0.76923	0.69231
		Norway	0.72727	0.58333	0.15385	0.15385	0.15385	0.38462
		Portugal		0.41667	0.38462	0.38462	0.30769	0.30769
		Spain	0.27273	0.50000	0.53846	0.53846	0.69231	1.00000
		Sweden	0.90909	0.91667	0.46154	0.61538	0.23077	0.61538
		Switzerland			0.61538	0.46154	0.38462	0.46154
		United Kingdom	0.63636	0.33333	0.84615	0.92308	0.84615	0.84615

Table 2.8: Z-score by Target and Placebo Models

	Type	Unit Name	FDI Per Capita	GNI PPP Per Capita	Mortality Rates (Simple)		Mortality Rates (Complex)	
			Both	Both	Female	Male	Female	Male
Z-score	Treated	Ireland	2.99386	3.16150	3.31371	3.32436	3.32656	3.16711
	Donor	Austria	-0.32527	-0.32977	-0.37855	-0.30855	-0.30537	-0.46291
		Denmark	-0.30841	-0.32935	-0.33461	-0.30615	-0.28761	-0.44828
		Finland	-0.37436	-0.27751	-0.17049	-0.20016	-0.30397	-0.01378
		France	-0.27225	-0.00723	-0.14273	-0.28002	-0.27934	-0.38745
		Italy	-0.38228	-0.37189	-0.32584	-0.30697	-0.29221	0.65699
		Netherlands	0.03116	-0.31768	-0.36559	-0.30329	-0.29859	-0.44104
		Norway	-0.36997	-0.30518	-0.07187	-0.14825	-0.20713	-0.24875
		Portugal		-0.28296	-0.27214	-0.28548	-0.24752	-0.22585
		Spain	-0.25289	-0.29831	-0.29815	-0.29135	-0.29689	-0.47718
		Sweden	-0.37873	-0.36200	-0.27570	-0.29514	-0.22571	-0.39087
		Switzerland			-0.31912	-0.29053	-0.27931	-0.26566
		United Kingdom	-0.36086	-0.27961	-0.35892	-0.30846	-0.30292	-0.46232

Table 2.9: Pre- and Post-Intervention MSPE by Target and Placebo Models

	Type	Unit Name	FDI Per Capita	GNI PPP Per Capita	Mortality Rates (Simple)		Mortality Rates (Complex)	
			Both	Both	Female	Male	Female	Male
Pre MSPE	Treated	Ireland	10,455.86561	966,346.84056	0.23532	0.02676	0.02622	0.17520
	Donor	Austria	121,811.33481	430,162.04485	4.12137	0.71634	4.99980	0.67311
		Denmark	49,757.53792	8,953,536.76930	2.67911	1.37709	1.73562	4.70123
		Finland	80,632.59346	13,716,759.82240	0.49427	0.57717	2.71091	0.49893
		France	6,998.66708	288,671.70456	0.63622	0.60131	0.83809	0.43269
		Italy	34,336.66556	16,936,413.99914	2.51200	0.36501	0.97805	0.04570
		Netherlands	79,111.26659	3,776,212.52463	1.57284	4.17004	4.60287	5.25344
		Norway	50,631.60748	84,766,161.14909	0.20379	0.30692	0.03587	0.39049
		Portugal		23,086,560.04082	2.54828	4.40863	0.93402	1.82060
		Spain	40,201.68789	24,286,621.74626	2.35507	3.91693	2.58211	3.39905
		Sweden	143,139.49776	2,715,278.95073	0.18236	0.15520	0.32461	1.15955
		Switzerland			2.71523	1.69094	1.43145	0.66537
		United Kingdom	52,229.95522	3,318,210.56583	1.81207	1.95571	2.18379	2.12082
Post MSPE	Treated	Ireland	219,436,772.98908	172,578,650.80901	4.21949	2.65598	2.88842	4.33680
	Donor	Austria	44,022,671.71598	1,147,098.48186	0.10433	0.09980	0.16622	0.08295
		Denmark	23,193,811.30460	24,066,228.94570	0.63883	0.28186	0.99251	1.04581
		Finland	4,543,915.13775	72,703,085.17016	0.51124	1.78734	0.20512	1.58193
		France	4,834,892.96211	5,461,521.36772	0.74373	0.55178	0.68947	0.27485
		Italy	244,363.57691	9,223,607.42752	0.70574	0.06657	0.42298	0.35289
		Netherlands	203,812,203.15628	12,370,436.11389	0.13871	1.17863	1.09929	1.42677
		Norway	4,232,033.18981	331,076,143.26794	0.30825	1.38508	0.10806	0.61554
		Portugal		116,022,547.67477	1.37954	3.38890	1.66942	3.15272
		Spain	32,609,875.65899	103,275,074.35420	0.97794	2.38393	0.75034	0.08977
		Sweden	4,178,889.35081	2,831,641.80455	0.09558	0.07840	0.79493	0.70970
		Switzerland			0.85142	1.06662	1.17861	0.97251
		United Kingdom	7,322,333.22306	17,235,620.44087	0.21841	0.27710	0.23507	0.26978
MSPE Ratio	Treated	Ireland	20,986.95423	178.58873	17.93119	99.26145	110.15981	24.75368
	Donor	Austria	361.40045	2.66667	0.02532	0.13931	0.03325	0.12323
		Denmark	466.13664	2.68790	0.23845	0.20468	0.57185	0.22245
		Finland	56.35333	5.30031	1.03434	3.09675	0.07566	3.17064
		France	690.83054	18.91949	1.16898	0.91764	0.82267	0.63522
		Italy	7.11670	0.54460	0.28095	0.18238	0.43247	7.72198
		Netherlands	2,576.27279	3.27588	0.08819	0.28264	0.23883	0.27159
		Norway	83.58481	3.90576	1.51261	4.51284	3.01227	1.57631
		Portugal		5.02555	0.54136	0.76870	1.78735	1.73169
		Spain	811.15688	4.25234	0.41525	0.60862	0.29059	0.02641
		Sweden	29.19452	1.04285	0.52411	0.50512	2.44886	0.61205
		Switzerland			0.31357	0.63078	0.82336	1.46161
		United Kingdom	140.19413	5.19425	0.12053	0.14169	0.10764	0.12721

Table 2.10: Pre- and Post-Intervention RMSPE by Target and Placebo Models

	Type	Unit Name	FDI Per Capita	GNI PPP Per Capita	Mortality Rates (Simple)		Mortality Rates (Complex)	
			Both	Both	Female	Male	Female	Male
Pre RMSPE	Treated	Ireland	102.25393	983.02942	0.48509	0.16358	0.16193	0.41857
	Donor	Austria	349.01481	655.86740	2.03012	0.84637	2.23602	0.82043
		Denmark	223.06398	2,992.24611	1.63680	1.17350	1.31743	2.16823
		Finland	283.95879	3,703.61443	0.70304	0.75971	1.64648	0.70635
		France	83.65804	537.28177	0.79764	0.77544	0.91548	0.65779
		Italy	185.30155	4,115.38747	1.58493	0.60416	0.98897	0.21377
		Netherlands	281.26725	1,943.24793	1.25413	2.04207	2.14543	2.29204
		Norway	225.01468	9,206.85403	0.45143	0.55400	0.18940	0.62490
		Portugal		4,804.84756	1.59633	2.09967	0.96645	1.34930
		Spain	200.50359	4,928.14587	1.53462	1.97912	1.60690	1.84365
		Sweden	378.33781	1,647.81035	0.42704	0.39396	0.56975	1.07682
		Switzerland			1.64779	1.30036	1.19643	0.81570
		United Kingdom	228.53874	1,821.59561	1.34613	1.39847	1.47777	1.45630
Post RMSPE	Treated	Ireland	14,813.39843	13,136.91938	2.05414	1.62972	1.69954	2.08250
	Donor	Austria	6,634.95831	1,071.02684	0.32301	0.31590	0.40770	0.28800
		Denmark	4,815.99536	4,905.73429	0.79927	0.53091	0.99625	1.02265
		Finland	2,131.64611	8,526.61042	0.71501	1.33691	0.45290	1.25775
		France	2,198.83900	2,336.98981	0.86240	0.74282	0.83034	0.52426
		Italy	494.33144	3,037.03925	0.84008	0.25801	0.65037	0.59404
		Netherlands	14,276.28114	3,517.16308	0.37244	1.08565	1.04847	1.19447
		Norway	2,057.19061	18,195.49788	0.55520	1.17690	0.32872	0.78456
		Portugal		10,771.37631	1.17454	1.84090	1.29206	1.77559
		Spain	5,710.50573	10,162.43447	0.98891	1.54400	0.86622	0.29961
		Sweden	2,044.23319	1,682.74829	0.30916	0.27999	0.89159	0.84244
		Switzerland			0.92273	1.03277	1.08564	0.98616
		United Kingdom	2,705.98101	4,151.58048	0.46734	0.52640	0.48484	0.51941
RMSPE Ratio	Treated	Ireland	144.86875	13.36371	4.23452	9.96300	10.49570	4.97531
	Donor	Austria	19.01054	1.63299	0.15911	0.37325	0.18233	0.35104
		Denmark	21.59020	1.63948	0.48831	0.45242	0.75621	0.47165
		Finland	7.50689	2.30224	1.01703	1.75976	0.27507	1.78063
		France	26.28366	4.34965	1.08119	0.95794	0.90701	0.79701
		Italy	2.66771	0.73797	0.53004	0.42706	0.65762	2.77884
		Netherlands	50.75700	1.80994	0.29697	0.53164	0.48870	0.52114
		Norway	9.14247	1.97630	1.22988	2.12434	1.73559	1.25551
		Portugal		2.24177	0.73577	0.87675	1.33692	1.31594
		Spain	28.48082	2.06212	0.64440	0.78014	0.53906	0.16251
		Sweden	5.40320	1.02120	0.72395	0.71072	1.56488	0.78233
		Switzerland			0.55998	0.79422	0.90739	1.20897
		United Kingdom	11.84036	2.27909	0.34718	0.37641	0.32809	0.35666

Reforming Council Tax in England: Empirical Evidence and Reform Options for a Fairer Property Tax System

Abstract

Council Tax in England is increasingly misaligned with the property market, embedding structural inequities and fiscal inefficiencies. The system remains anchored to 1991 valuations, and the fixed banding structure has built-in regressive features in which higher-value dwellings face disproportionately low effective tax rates relative to their market prices. This paper develops an empirical framework to evaluate these distortions and simulate revenue-neutral reform options using modern statistical methods. A comprehensive, property-level dataset was constructed by linking sales transaction records, property attributes, and tax liabilities. Contemporary property values were then estimated via a machine learning–based Automated Valuation Model (AVM), producing a statistical revaluation benchmark that aligns liabilities with current market conditions. Building on this, 14 counterfactual tax structures are simulated, ranging from modest adjustments to the band system (e.g., additional upper bands or recalibrated multipliers) to more fundamental restructuring, including decile-based and continuous value-based tax schedules.

The simulations reveal that over half of dwellings in England are mis-banded under the current system, largely due to divergent property price growth since 1991. Revaluation alone delivers the largest equity gains across all reforms, correcting long-standing misallocations and substantially improving the alignment between tax liabilities and property values. However, these gains are inherently disruptive, as updating valuations results in widespread reassignment of properties and significant redistribution of tax liabilities across households and regions. Even with updated values, the banding structure itself remains regressive. Additional gains arise from reweighted multipliers or expanded band systems that better align tax rates with property values while preserving a degree of stability. Fully ad valorem models achieve the most proportional outcomes but may pose political and practical challenges, particularly due to large increases for the highest-value properties and greater sensitivity to valuation precision.

Importantly, the analysis demonstrates that large-scale, statistically robust revaluation is feasible using only public data. These findings provide policymakers with a flexible, evidence-based framework for improving equity and efficiency in a politically sensitive area of tax policy, highlighting that the primary gains from reform arise from updating valuations, while the design of the tax structure determines how resulting redistribution is distributed and managed. Overall, even modest reforms, when anchored in current valuations, can materially improve fairness while maintaining fiscal neutrality.

1 Introduction

Property taxes are broadly considered to be among the most stable and equitable sources of local government revenue, supporting essential services including social care, education, public transportation, and emergency response. Nevertheless, the effectiveness of property taxation is contingent upon the design of the system and its ongoing adjustment to reflect evolving market conditions. Council Tax, the main residential property tax in England, Scotland, and Wales, was introduced in 1993, and properties were taxed based on an estimate of their 1991 values. Since then, England has not undergone a general revaluation, meaning current tax bills are still based on property values from over three decades ago (Adam & Browne, 2006; Alma Economics, 2023; Sandford, 2025). An optimally structured property tax would dynamically adjust with the market, ensuring that higher-value properties contribute proportionately more to revenues in line with households' ability to pay and the property's value. By contrast, the UK's static banding system assigns each property to a fixed value band with predetermined tax charges. As a result, liabilities cannot reflect current market conditions. As a result, many properties with similar market values end up facing dramatically different Council Tax bills, raising serious concerns about equity and efficiency (Murphy, Snelling, & Stirling, 2018).

1.1 Key Issues with the Existing System

This paper explores two fundamental weaknesses currently plaguing the Council Tax system in England: the lack of valuation updates and the design of the banding structure itself. The first is well-established as a fundamental problem; over the nearly 35 years since the last revaluation date, property price fluctuations have been asymmetrical, especially along geographic lines. London and the Southeast have experienced significantly greater property price inflation since the early 1990s, driven by strong population growth, constrained housing supply,

and their elevated global economic role.²⁹ Without revaluations, southern residents, especially those living in high-value properties, pay a lower relative tax rate (benchmarked against the value of their property, as well as income). By contrast, lower-value properties in the North and Midlands bear a greater tax burden relative to their worth. It is common to observe high-value properties in London and more modest value properties in the North or Midlands that had a similar 1991 valuation and thus fall into the same tax bands and have similar (though not identical) tax liabilities. This undermines the principle of proportional taxation and exacerbates geographic inequities (Hills, 2007; Adam, Hodge, Phillips, & Xu, *Revaluation and Reform: Bringing Council Tax in England into the 21st Century*, 2020; Neidle & Byrne, 2024; Adam & Browne, *A Survey of UK Tax System*, 2006; Murphy, Snelling, & Stirling, 2018).

The lack of revaluation not only places uneven pressures on households with relatively high deprivation, but it leads to funding challenges for local authorities, who have increasingly relied on Council Tax as a revenue source (Murphy, Snelling, & Stirling, 2018). Additionally, beyond regional inequity concerns, stagnant valuation also creates distortions for new housing communities. Homes built after 1991 must be assessed as though they existed in 1991, leading to estimated backdated valuations that often misclassify properties into inappropriate bands. This is especially true when no surrounding benchmarks can be found, meaning when most regional development occurred after 1991.

The stagnant valuations are not the only challenge with the current Council Tax system, nor are they the only driver of inequity. The second obstacle is the banding system itself (in which households are placed into a tax band with a mostly fixed liability based on the assessed value of the property). While the banding system was

²⁹ This trend has shown signs of reversal since around 2016, as cities in the North of England, such as Manchester and Leeds, have seen comparatively faster price growth in percentage terms. Contributing factors include increased investment under the government's 'levelling up' agenda, the post-pandemic rise in remote working, and a relative cooling of London's overheated market.

structurally designed to support some imprecision in assessments without resulting in liability changes, the system was not designed to handle the level of imprecision that has come with out-of-date valuations. More notably, the bands themselves are often criticized for imposing a fixed, regressive structure with capped multipliers (ratios charged to the band relative to band D) and wide valuation ranges that fail to reflect current market realities. Even with perfect valuations, the current bands would impose lower effective tax rates on high-value properties and higher rates on those at the bottom (Jones, Leishman, & Orr, 2006; Plimmer, McCluskey, & Connellan, 1999; Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020). This is not merely an artifact of time but a built-in structural inequity that has long raised concerns since the introduction of the Council Tax system (Jones, Leishman, & Orr, 2006).

A range of international property tax systems offer instructive contrasts to the UK model, including countries that use regular revaluations, proportional tax rates, or progressive structures. A more detailed comparison is provided in Appendix A.

1.2 Approach and Results

This study empirically addresses the question: how would alternative Council Tax reforms affect the equity, proportionality, and spatial distribution of tax liabilities if properties were valued using contemporary market conditions? This question is evaluated by separating two broad sources of distortion. These two sources are the misalignment created by retaining 1991 valuations despite uneven property price growth, and the regressivity embedded in the banded tax schedule itself. The central objective is therefore not only to estimate updated property values, but to assess how different reform designs change the relationship between tax liabilities, property values, local geography, and indicators of household need. To answer this, a comprehensive property-level dataset for England was constructed by linking HM Land Registry sales data, Energy Performance Certificate (EPC) property attributes, and Council Tax band and liability data. After cleaning and imputing missing features through deterministic and machine learning methods, contemporary property values are

estimated using a geographically weighted Random Forest model. Effectively, an AVM based on public data is used to create a statistical reassessment of properties in England. For properties without a sale history, prices are imputed using observed or imputed features.

Using these updated valuations, various counterfactual tax structures are simulated with properties allocated into different bands or tax brackets. Rather than endorsing one reform approach, this study examines 14 alternative tax structures in comparison to the current system, a simple revaluation, and to each other. These scenarios represent only a subset of the many potential system reforms. However, they broadly illustrate the impacts of both minor and major changes. These 14 scenarios can be broadly categorised into five primary categories:

1. **Revaluation Only:** Updates property values while keeping the band structure and multipliers unchanged.
2. **Reweighted Multipliers:** Retain the existing band structure but adjust the multipliers to change relative liabilities across bands.
3. **Band Structure Reforms:** Expand the number of bands to allow for finer differentiation by property value.
4. **Hybrid Band Value:** Combine additional bands with adjusted multipliers to enhance progressivity.
5. **Value-Based Tax Systems:** Replace the banding system with liabilities tied directly to assessed property values (e.g., flat or progressive mill rates).

Each simulation generates a counterfactual and is evaluated on distributional fairness, tax proportionality at both local and national levels, and household-level impacts (e.g., the number of “winners” and “losers” created by the reform). This approach enables direct comparison of structural reforms (such as expanding or narrowing bands) alongside valuation updates and allows the effects of each component to be isolated.

Within this framework, proportionality describes the degree to which tax liabilities correspond with estimated property values, while progressivity examines whether properties of higher value incur higher effective tax rates compared to those of lower value. The current system may exhibit nominal progressivity in liabilities but

regressivity in effective rates. Therefore, the analysis concentrates on the implicit tax rate, which is defined as Council Tax liability divided by estimated property value. This approach clarifies the primary outcome; reforms are evaluated based on their capacity to narrow the disparity between tax liabilities and current property values, enhance the alignment between tax burdens and indicators of ability to pay, and mitigate spatial inequities across local authorities.

The results of the counterfactual simulations reveal the scale and structure of misalignment in the current Council Tax system. In this study, it is estimated that over half of all dwellings in England are mis-banded, primarily as a consequence of differential property price inflation since 1991. Revaluing the property base and redistributing dwellings into their appropriate bands yields immediate and substantial equity gains. A majority of households would experience net annual savings, and these gains are disproportionately concentrated in lower-income and more deprived areas, reflecting long-standing distortions embedded in the 1991 valuations. In fact, most of the equity improvements observed across all reforms stem from this first-order correction, that is, from updating property values and reallocating properties into appropriate bands at the national level. Even a more limited re-banding at the local authority level substantially increases tax rate proportionality by aligning liabilities more closely with current market values

These effects are further reinforced when liability structures are adjusted to be more proportional to assessed property values. Simulations imposing stronger proportionality (through the addition of new upper bands, value-weighted multipliers, or a full transition to an ad valorem mill levy) deliver the largest distributional shifts. By contrast, incremental changes, such as adding a single top band, produce only partial improvements. The magnitude of these effects is closely tied to the degree of structural disruption introduced by the reform: the more closely liabilities track actual property values, the greater the gains in both horizontal and vertical equity.

These findings remain robust after accounting for Council Tax Reduction (CTR) schemes and related discounts and exemptions (collectively referred to as CTS in this study). While some reforms retain the existing

CTS framework, others adjust or replace it entirely. Although CTR plays an important role in mitigating tax burdens for low-income households, administrative complexity, variable take-up rates, and uneven targeting limit its effectiveness in offsetting the underlying inequities of the current tax base. As noted in previous work (Jones, Leishman, & Orr, 2006).

1.3 Contribution of this Study

This research makes a substantive contribution to the literature on property taxation, public finance, and applied policy simulation. It provides a national-scale empirical simulation of alternative Council Tax structures grounded in property-level, machine learning-based valuation estimates. This is not simply a technical exercise in updating property values. Rather, it develops a policy-relevant framework for evaluating the distributional, spatial, and equity implications of structural tax reform.

The contribution lies in both the scale of the analysis and the structure of the simulation framework. Unlike prior studies, which have typically examined localised reforms or relied on population samples, this study leverages a comprehensive national dataset and modern valuation methods to operationalise competing reform strategies, ranging from simple revaluation to band restructuring and fully value-based systems. Each reform is modeled under a common valuation baseline, allowing the analysis to distinguish the effects of revaluation from the effects of changing the tax schedule itself. This makes it possible to compare the mechanisms through which different reforms shape tax burdens across property values, local authorities, and household groups.

The contribution also lies in its granularity and replicability. The simulations encompass over 23 million dwellings across England, incorporating fine-grained geographic variation in property values and local fiscal settings. This level of coverage enables robust assessment of both horizontal and vertical equity impacts at multiple spatial scales. The methodological pipeline, which links administrative datasets, imputes missing property characteristics, and applies a geospatial Random Forest-based automated valuation model, demonstrates

how established empirical techniques can make nationwide tax reform analytically tractable, transparent, and replicable without reliance on proprietary data.

Importantly, the study does not seek to prescribe a single optimal reform path, nor does it claim perfect precision in property valuation. Instead, it establishes a robust empirical and methodological foundation for evaluating alternative reform options. The simulations are designed to illustrate the mechanisms and consequences of different structural choices, not to deliver definitive forecasts of policy outcomes. The valuation model is a transparent statistical approximation, sufficient for exploring policy space but not a substitute for formal administrative valuations.

Finally, the study directly addresses a pressing policy question. Organizations such as the Institute for Fiscal Studies, most notably Adam et al. (2020)³⁰, have demonstrated the substantial equity gains achievable through revaluation using microdata-based simulation, with particular emphasis on the distributional consequences of updating 1991 valuations. Their work establishes the central importance of revaluation, while considering a more limited set of structural reforms. This study extends that framework by applying a property-level simulation to a near-complete dataset of dwellings and by systematically evaluating a broader set of counterfactual tax structures under a common valuation baseline. In doing so, it provides operational, data-driven evidence on the distributional and spatial consequences of reform at the national level. By combining modern valuation techniques with a

³⁰ Adam et al. (2020) evaluate the distributional consequences of Council Tax revaluation in England using survey-based microdata and microsimulation techniques. Their analysis demonstrates that updating 1991 valuations to contemporary prices would generate substantial redistribution across households and regions, particularly reflecting differential property price growth. However, their approach is based on a representative sample rather than a near-complete property-level dataset and focuses primarily on revaluation with a limited exploration of alternative tax structures. In contrast, this study employs a machine learning-based Automated Valuation Model applied across the full housing stock and systematically evaluates a broader set of counterfactual tax designs under a consistent valuation framework. Despite these methodological differences, both analyses arrive at a consistent central conclusion: that the majority of equity gains arise from revaluation itself, while the design of the tax structure determines how those gains are distributed and whether underlying regressivity is fully addressed.

counterfactual simulation architecture, the research offers policymakers a practical and scalable framework that can be refined, extended, or adapted to support transparent, equitable, and evidence-based Council Tax reform.

2 Council Tax Background

The Council Tax system was established in 1993, replacing the poll tax (Community Charge) system. [A more detailed history of the Council Tax system can be found in Appendix A.] Subsequent legislative reforms have primarily addressed administrative aspects and incremental changes to equity. Structural modifications that have occurred were generally specific to England, Wales, or Scotland, resulting in some notable differences among the systems over time. Wales has enacted the most significant change to the original Council Tax structure. Scotland only obtained an independent Council Tax system with the enactment of the Scotland Act 1998 in 1999, which created the Scottish Parliament and devolved significant powers from Westminster to Holyrood. While the SAA was in place prior, Scotland was then responsible for the Council Tax structure, local government finance and grants, and CTR. While Scotland has not enacted large changes since, they have targeted keeping Council Tax lower for more deprived areas. England, on the other hand, has remained largely unchanged if not more fractured due to devolution of responsibilities to the local level.

2.1 2005 Reforms in Wales

The first major divergence arose when Wales added a ninth band (Band I) at the top end in 2005 (Adam & Browne, 2006; Adam, Hodge, Phillips, & Xu, Revaluation and Reform of Council Tax in Wales, Impacts on Different Council and Household Types, 2020). Scotland has similarly explored adding additional bands at the top or bottom ends to ensure that the highest and/or lowest bands aren't as wide or are fairer. In fact, recent studies suggest that there are contemporary inquiries into band expansions as a component of current reform efforts in both Scotland and England, but only Wales has altered bands thus far (Adam, Phillips, & Ray-Chaudhuri, Scottish Council Tax: Ripe for Reform, 2025; Jones, Leishman, & Orr, 2006).

At the time that Band I was added, Wales also implemented the only revaluation that has occurred in the UK. This shifted the valuation anchor date to April 1, 2003 which significantly improved the accuracy of assessment at the time (Adam & Browne, 2006; Adam, Hodge, Phillips, & Xu, Revaluation and Reform of Council Tax in Wales, Impacts on Different Council and Household Types, 2020).³¹ Additionally, this Act affirmed a cyclical revaluation of every 10 years in hopes of maintaining pricing accuracy. It's notable that periodic revaluation was still expected at the time; in fact, England was slated to reassess properties in 2007. English revaluation was then reinforced when the central government commissioned The Lyons Inquiry into Local Government in 2004, an independent evaluation of value and effectiveness of Local government led by Sir Michael Lyons and conducted by the Centre for Local Economic Strategies (CLES). In short, the report argued for more autonomy and financial control for local Councils. In terms of Council Tax, the paper argued in favor of reforms, including additional bands and periodic revaluation, citing that a revaluation and more bands could make the “system fairer” without the need for a Council Tax system replacement (Lyons, 2007). This was a landmark study but was ultimately outweighed by political concerns. The revaluation in Wales had increased a significant portion of the population's tax liabilities, which led to media denigration. Furthermore, the Chancellor of the Exchequer, Gordon Brown, was hesitant to make sweeping changes due to fear of alienating the middle class. As a result, England, Wales and Scotland completely abandoned revaluation plans following the enactment of the Council Tax (New Valuation Lists for England) Act 2006 (Murdie & Moorhouse, 2021; Adam & Browne, Reforming Council Tax Benefits: IFS Commentary C123, 2012).

³¹ Wales revaluation in 2005 was implemented under the Council Tax (Valuation Bands) Order 2003 as mandated by the Local Government Act 2003 (The Council Tax (Valuation Bands) Order, 2005).

2.2 Rate Setting and Adjustment

The next divergence between the three countries is in terms of liability levels. England and Wales have seen consistent annual increases in Council Tax rates, while Scotland implemented extended freezes between 2008 and 2017. During the freeze, Scottish local authorities were compensated by the central Scottish government for the revenue they would have otherwise raised by increasing Council Tax (University of Strathclyde, 2023; Mirrlees, et al., 2014). After the freeze ended, Scotland introduced modest reforms targeting Council Tax, such as increasing the tax rate multiplier for the higher-value bands (E through H) while keeping the lower bands' multipliers unchanged. These adjustments introduced a slight degree of additional progressivity into the system, but critics argue that they failed to address the underlying structural issues stemming from outdated valuations and broad band ranges (Alma Economics, 2023; Adam, Phillips, & Ray-Chaudhuri, Scottish Council Tax: Ripe for Reform, 2025; Murdie & Moorhouse, 2021).

Near the beginning of the Council Tax freeze period in Scotland, the devolution of centralised powers to more local control occurred with the passage of the Localism Act of 2011. While paving the way for later devolution, it mainly gave localities across the UK control over rate setting and adjustment. Prior, the central government would review and could override rate change decisions, but this control mechanism was replaced by a referendum-based approach. Under this system, year-over-year changes to the Band D rate can be adopted subject to a cap. In England and Wales, that cap is generally set at 3% with an extra 2% permitted for authorities with adult social care responsibilities.³² Any additional increases beyond this threshold must be approved via a local referendum. This both represented a divesting of central powers but while adding a check to prevent

³² Currently, 152 authorities in England had adult social care responsibilities, and nearly all of them utilize some of all of the additional 2% precept for social care (Department for Levelling Up, Housing & Communities, 2024).

excessive taxation and system shocks without direct public consent (Department for Levelling Up, Housing & Communities, 2024).

In cases where Councils face acute financial pressures and would rather bypass holding a local referendum (often because it would likely not pass), the central government can still grant special permission to exceed the cap without a vote. These are generally rare and usually require an issuance of a Section 114 notice, in which the Chief Financial Officer for a local authority argues that the Council is unable to meet its legal duty to balance its budget, effectively indicating that the authority is at risk of insolvency. Despite many requests, only Bradford, Newham, Windsor & Maidenhead, Birmingham, Somerset, and Trafford were granted exceptions in 2025–26. These six exceptions permitted Council Tax increases between 7.49% and 9.99% to help manage social care and budget pressures. A far more common strategy is for Councils to routinely increase rates just below the referendum trigger. Only 29 Councils in England have proposed increases below 4.99%, with just 20 keeping rates below 4.00% (Wells, 2025). [See Map 1 in Appendix B.]

2.3 Council Tax Support (CTS)

The final divergence in the Council Tax system is also the most significant. The regressive structure cannot be fully accounted for without considering the role of Council Tax Reduction (CTR) in providing relief to lower income households that often occupy cheaper dwellings. By 2013, nearly six million households relied on the Council Tax Benefits (CTB) - the predecessor to the current CTR scheme – making it a critical tool for promoting vertical equity. However, it also garnered a lot of public criticism, as it was costly to administer and was seen as lacking transparency. Additionally, CTB was criticised for contributing to high Effective Marginal Tax Rates (EMTRs), meaning that as individuals earned more, their benefits were withdrawn at a rate that significantly reduced the financial gains from employment. Concerns were that this disincentivised workers to earn more or pursue advancement (Adam & Browne, 2010). More importantly, policymakers sought to shift welfare funding responsibility to local authorities as part of broader efforts to decentralise decision-making and promote fiscal

accountability (Adam & Browne, 2010; Ayrton, Holden, & Kenway, 2022; Hoynes, Joyce, & Waters, 2023; Murdie & Moorhouse, 2021). Thus, following a 2010 Spending Review, the Welfare Reform Act 2012 repealed and replaced CTB (Murdie & Moorhouse, 2021; Ayrton, Holden, & Kenway, 2022; House of Commons Library, 2012; Welfare Reform Act, 2012).

While CTR was devolved to the local level in England, Wales and Scotland approached CTR uniquely. In England, local authorities are required to establish their own reduction schemes, with flexibility to design eligibility criteria and benefit levels within a constrained budget. The over 300 local authorities are responsible for billing, collection, enforcement, and administering relief schemes such as discounts and exemptions (Department for Levelling Up, Housing and Communities, 2024). The constrained budget was still centrally controlled. Initially fixed grants were earmarked for CTR and based on their prior respective CTB levels. However, CTR funding was aggregated into Revenue Support Grants (RSG) in subsequent years.³³ While the intention was to make it easier for localities to flex funds where needed most, some argued that bundled RSGs meant that Councils could no longer track exactly how much money was allocated to CTR, meaning it competed with other localities for funding. Additionally, unlike CTB, CTR was no longer funded at full cost. Compared to the prior year, funding decreased by 10% in the first year. This translated to a £410 million reduction in England alone (Adam & Browne, 2012; Ayrton, Holden, & Kenway, 2022). Pensioners remained protected by statute, but working-age claimants faced varying support levels depending on local policy. Because Councils were then responsible for funding the shortfall, disparities in the level of support available across different regions formed. In contrast to England, Scotland and Wales retained a more centralised system with the central governments

³³ The Welfare Reform Act 2012 also created the Universal Credit (UC), which replaced six legacy benefits, including Income Support (IS), Income-based Jobseeker's Allowance (JSA), Income-related Employment and Support Allowance (ESA), Housing Benefit (HB), Child Tax Credit (CTC), and Working Tax Credit (WTC). While some have argued for CTR to be rolled into UC to make means-tested social benefits more streamlined, this would be effectively undo the decentralization of CTR and would be challenging to implement, given the individual structure of each local authorities CTR scheme.

continuing to fund a nationally consistent CTR scheme (Ayrton, Holden, & Kenway, 2022). [See Appendix A for a discussion on the CTB to CTR shifts in Wales and Scotland for comparison.]

Today, CTR and other discounts and relief schemes [collectively referred to as Council Tax Support (CTS) in this study] represents a significant reduction in Council Tax collection. The Office for Budget Responsibility estimates that the net Council Tax revenue in England (post all discounts and exemptions) is approximately £46 billion per year, representing about a quarter of local authorities' spending (Office for Budget Responsibility, 2024). Estimated gross revenue, without discounts or exemptions, could be around £55 billion, roughly 20% higher (Adam & Browne, Reforming Council Tax Benefits: IFS Commentary C123, 2012). Aggregating 2024 figures available from the Ministry of Housing, Communities & Local Government, we see that there are 25.68 million dwellings in England, though some of these are non-taxable. Aside from CTR, the Single Adult Discount is the most prolific discount, which impacts 8.41 million dwellings. This discount impacts the lower band greater than the higher bands with about 47% of Band A dwellings receiving the discount, compared to only 10% of Band H. In fact, each band has a significantly lower percentage of Single Adult occupiers than the previous band.

2.4 Equity and Efficiency Challenges in the Current System

CTS Reforms

While CTS mitigate some of the regressive impacts of England's outdated Council Tax system and provides relief for qualifying and often needy property owners, it does not eliminate structural regressivity. Even with CTS, households in lower-value homes continue to pay higher effective tax rates relative to their property value than those in high-value properties. The complexity of CTS administration, fragmented local scheme design, and limited automatic enrollment contribute to low take-up rates, with as many as one-third of eligible households failing to claim benefits. The result is an incomplete and unevenly distributed safety net, particularly among vulnerable populations and in lower-income regions. These limitations underscore the importance of structural

reform to the tax base itself, rather than continued reliance on post hoc relief mechanisms. [See Appendix A for a fuller discussion of CTS complexity, take-up rates, and income targeting challenges.]

Revaluation of Dwellings throughout England

Beyond CTS, the more fundamental issue lies in the absence of property revaluation. The Council Tax system remains anchored to 1991 valuations despite dramatic shifts in housing markets since that time. Properties in London have seen values increase nearly six-fold, while growth in northern England and the Midlands has been substantially lower, leading to geographic tax inequities unrelated to current property worth. This decoupling of tax liabilities from contemporary market values creates fiscal inefficiencies, undermines equity, and impairs transparency. In many cases, similar properties face divergent tax bills simply due to outdated assessments or inconsistent local rate-setting. Misalignment with current values also limits Councils' ability to respond to shifting service demands and revenue needs. [See Appendix A for more detail on valuation disparities, geographic misalignments, and market evolution since 1991.]

While some degree of lag between valuations and market conditions can be expected in any property tax system, prolonged gaps (such as the three-decade freeze on Council Tax valuations) exacerbate inequities and distortions. Traditional assessment methods suggest that revaluations should be undertaken on three-to-five-year cycles to maintain alignment with market conditions and avoid extreme distortions (Plimmer, McCluskey, & Connellan, 1999; Adam, Phillips, & Ray-Chaudhuri, *Scottish Council Tax: Ripe for Reform*, 2025). The Welsh government has recently legislated for an initial revaluation by 2028 and default five-year revaluation cycles thereafter (Adam, Phillips, & Ray-Chaudhuri, 2023). Traditional periodic revaluation cycles can offer a degree of stability and dampen short-term shocks by smoothing valuations through multi-year weightings. However, as time passes between revaluations, the accuracy of the tax base erodes, and inequities widen between regions and households. In rapidly changing housing markets, this widening misalignment becomes particularly acute.

In this context, the adoption of modern automated valuation approaches presents a promising structural solution. Automated Valuation Models (AVMs) allow for more frequent, cost-effective revaluations that keep tax systems aligned with current market conditions while permitting flexible implementation cycles. AVMs leverage statistical and machine learning methods to improve accuracy, consistency, and replicability compared to classical appraisal approaches (Ho, Tang, & Wong, 2021; Mu, Wu, & Zhang, 2014). Real-world case studies demonstrate the feasibility of AVM use at scale; the Netherlands, for instance, was revaluating about 8.5 million properties annually in 2014 using computer-assisted mass appraisal, which is deemed “the only approach” efficient enough to meet yearly valuation requirements at that scale (Netherlands Council for Real Estate Assessment, 2014). They continue to use these AVMs. This demonstrates that automated mass valuation has already enabled jurisdictions to maintain up-to-date, high-quality tax rolls and without a large labor force. [A more comprehensive discussion on the advantages of AVMs can be found in Appendix A.]

Banding System Reweights or Revisions

Beyond outdated assessments, the structure of the Council Tax banding system imposes disproportionate burdens on residents of lower value properties, even within the lowest bands. Tax liabilities are not strictly aligned with property valuations, leading to significant disparities across the valuation spectrum. The regressivity is highlighted when comparing the bookend bands; Band H properties often incur slightly higher tax charges than Band A properties, despite representing significantly greater market worth. The lack of granularity within bands, along with wide band valuation ranges, further compounds horizontal inequity, especially for households near band thresholds. Without structural reforms to the band design (such as narrowing ranges, adding new upper bands, or shifting to a continuous value-based tax) Council Tax will remain misaligned with both ability to pay and modern property distributions. [Appendix A provides additional evidence on band-based regressivity and the distributional impacts of the current structure.]

There has been extensive discussion regarding the reform of the banding structure. Common proposals include updating valuation band sizes or multipliers to more accurately reflect property prices, introducing new bands (particularly at the higher and lower ends) to better match the current distribution of property values, or replacing the banded system entirely with a continuously proportional tax based on current property values (Adam & Browne, 2010; Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020; Adam, Phillips, & Ray-Chaudhuri, Scottish Council Tax: Ripe for Reform, 2025; Adam & Browne, Reforming Council Tax Benefits: IFS Commentary C123, 2012; Department for Communities and Local Government, 2012; Jones, Leishman, & Orr, 2006). Each option comes with an array of complexity, though they vary in their ambition and political feasibility (discussed in the next section). Nevertheless, the central objective for each reform is to align the tax base with a household's ability to tender their tax liabilities.

Political Feasibility and Other Reform Considerations

Naturally, political feasibility remains one of the central constraints on Council Tax reform. Evidence from recent consultations in Wales and Scotland highlights strong public resistance to full-scale revaluations but comparatively greater support for more incremental measures, such as introducing additional bands or revising existing thresholds (Welsh Government, 2022; Plimmer, McCluskey, & Connellan, 1999). Survey responses emphasise concerns over fairness, financial impacts, and the perceived unpredictability of future liabilities, especially among households in higher bands. Regional disparities further shape political dynamics; areas with slower price growth may experience tax reductions, while high-value regions could face increases, creating uneven incentives across constituencies (Adam, Hodge, Phillips, & Xu, 2020). These factors suggest that politically viable reforms are likely to favor gradual adjustments over abrupt systemic change, reinforcing the need for carefully structured implementation strategies to minimise resistance and distributional shocks. [Further detail on political barriers and public attitudes toward reform is provided in Appendix A.]

Furthermore, regardless of the reform details, implementation is key, and several elements are consistently emphasised in policy proposals. Transitional relief mechanisms are often used to phase changes in gradually, softening sudden increases in tax bills and providing households time to adjust to new costs. Because such phasing can create short-term revenue gaps, most proposals include either self-funding approaches, where those that win in the reform and those that lose in the reform experience phased rate changes symmetrically. Alternatively, another option is that the central government provides grants to support local authorities during the phase in process. In parallel, measures such as expanded Council Tax Reduction schemes or deferral programs are used to assist vulnerable and low-income households by allowing eligible individuals to postpone payments. These policies aim to address considerations of equity, fiscal stability, and political feasibility, so that reforms are both well-structured and practical to implement. [A further discussion on transitional design options, fiscal mechanisms, and international examples is provided in Appendix A.]

3 Data and Sources

The analysis presented in this report relies entirely on publicly available datasets, primarily sourced from the Valuation Office Agency (VOA), HM Land Registry, Office for National Statistics (ONS), and the Ministry of Housing, Communities & Local Government. This approach ensures transparency, replicability, and feasibility for potential policy implementation by government agencies.

3.1 Primary Data Sources

VOA Property Address and Tax Band Data

The foundational dataset for this analysis originates from the Valuation Office Agency (VOA), providing detailed council tax band information for properties across England and Wales. Data from individual Local Authority Districts (LADs) were downloaded separately and subsequently consolidated into a single comprehensive dataset. Each property record is uniquely identified by a combination of a Unique Property Reference Number (UPRN)

and a row counter, accommodating multi-unit properties. While the UPRN serves as a precise identifier for individual dwellings, the combined identifier was created to ensure uniqueness across the dataset.

The VOA dataset includes key property attributes, such as postal addresses, postcodes, and geographic hierarchy details. Geographic regions are organised hierarchically, from Local Authority District (LAD) down to Middle Super Output Areas (MSOA), Lower Super Output Areas (LSOA), and Output Areas (OA), aligning with the latest boundaries from the 2021 Census. Importantly, the dataset records the original council tax bands assigned based on property valuations from 1991 for England and 2003 for Wales. Although Wales is included for comparative purposes, the primary analysis focuses on England due to differences in valuation dates and property-market dynamics.

While the VOA dataset provides tax-band assignments, it does not include actual annual council tax liabilities for individual households. To estimate these liabilities, band-level charges were constructed using official local authority Band D rates as the base reference. The Band D charges were drawn primarily from the Live Tables on Council Tax published by the UK Government (GOV.UK). Because detailed charges for Bands A–H are not consistently available across all local authorities, statutory multipliers were applied to each Band D charge to derive corresponding liabilities for the remaining bands. These multipliers, uniform across England, reflect each band’s statutory proportion relative to Band D. Where local authorities were reorganised, the Band D charge of the new authority was used. If Band D data was missing, rates were obtained from other official sources, such as Council Tax levels set by local authorities in England 2023–24 (Table 8), CouncilTax.info, and direct publications from local authorities.

Although the VOA dataset contains detailed property counts by band and geography, exact replication of total council tax revenue by local authority was not feasible because the constructed band-level liabilities exclude certain exemptions, discounts, and parish-level precepts. Still, this method provides a consistent and transparent

framework for estimating council tax liabilities across England, suitable for comparative and distributional analysis.

To better approximate realised tax collections, a further adjustment was made using a Council Tax Scalar, which reflects the proportion of tax actually collected relative to the full theoretical liability. This scalar, denoted as RCR_i , is calculated for each LAD and tax band combination and captures the effect of Council Tax Support (CTS), which is again the collective Council Tax Relief (CTR) and other exemptions and discounts. Formally, each dwelling i is assigned the scalar corresponding to its band and LAD. Thus, the realised tax liability for that dwelling is defined as:

$$T_i = R_i \times RCR_{b,l}$$

Aggregating across all dwellings enables the computation of the Real Collection Ratio (RCR) and the Full Tax Equivalent Dwellings (FTED), which is the number of fully taxed dwellings that would yield equivalent revenue:

$$RCR = \frac{1}{N} \sum_{i=1}^N RCR_{b,l}$$

$$FTED = RCR \times N$$

, where $RCR_{b,l}$ = scalar based on Band b and LAD l

and N = total number of chargeable dwellings

and T_i = actual Council Tax collected for dwelling i

and R_i = full Council Tax potential for dwelling i

When accounting for only discounts and premiums, excluding CTR, there is a FTED of 22.85 million, implying a reduction of roughly 11%. By brand, non-CTR discounts and exemptions have a marginally greater impact on the lower bands; Band A has a RCR of 84.5%, while Band H has a RCR of 92.5%. When accounting for the combined CTS, we see FTED lowers further to 20.35 million, implying a total RCR of 79.3%. Comparatively, these numbers are similar to the roughly 20% estimate cited in Adam & Browne (2012). With all

discounts and relief, the distribution across bands is more favorable to the lower bands; Band A has a RCR of 64.7%, while Band H has a RCR of 92.2%. It is not, however, a linear increase from band-to-band. Band A and B received far more relief but there is only a 10% difference between Band C and Band H.³⁴

HM Land Registry Price Paid Data

To assess the adequacy of the current valuation framework, property transaction data was integrated from HM Land Registry, covering property sales in England and Wales since 1995. However, this dataset only includes transactions explicitly registered, resulting in incomplete coverage of all property transactions historically. Properties without transactions recorded since 1995, therefore, exhibit missing values, highlighting a notable limitation of the dataset.

The price paid dataset initially contained multiple transactions per property (resulting from repeated sales or complex property structures, such as apartment blocks with multiple units), resulting in duplicated records. To address this, the dataset was rigorously cleaned by retaining only the most recent completed transaction per property. Additionally, transactions involving non-traditional sales such as repossessions, property transfers among related parties, and incomplete transactions were excluded. This cleaning step significantly improved data accuracy and ensured reliable price histories for individual properties.

³⁴ England is fairly in line with the distribution observed in Scotland – as outlines in University of Strathclyde (2023) and based on the Scottish Government’s FAI calculations. Scotland has a slightly lower CRC of 75%. While the spread between Band A and Band E is larger (49% and 90% respectively), Scotland also has a significantly greater impact on the lower two or three bands than the others. The RCR, referred to as Billed Proportion (%) in University of Strathclyde (2023) and based on the Scottish Government’s FAI calculations, is as follows:

Band A	Band B	Band C	Band D	Band E	Band F	Band G	Band H	Total
49%	63%	71%	80%	86%	90%	92%	90%	75%

EPC Property Features Data

Additional property characteristics critical to valuation modeling were derived from Energy Performance Certificate (EPC) data. EPC datasets contain extensive property information, primarily emphasizing energy efficiency metrics. To mitigate multicollinearity and redundancy, a selective approach was adopted, retaining only key features demonstrably impacting property values and routinely employed by VOA valuations. Specifically, the retained EPC attributes include:

- **Property Status:** New build or existing property
- **Tenure Duration:** Freehold or Leasehold
- **Property Type:** Flat, House, Bungalow, Maisonette, Park Home
- **Build Form:** Detached, Semi-detached, End-terrace, Mid-terrace, Enclosed variations
- **Tenure Type:** Owner-occupied, Private rented, Social rented
- **Construction Age Band:** Categorised historical periods from pre-1900 to post-2003
- **Energy Efficiency Score:** Scaled 1–100, with higher scores indicating superior efficiency
- **Floor Area:** Total property area measured in square meters

The deliberate exclusion of property attributes, such as the number of bedrooms, demonstrates the mitigation of collinearity through feature limitation. Particularly, analysis indicated diminishing sensitivity of property values to bedroom count in high-value properties, with floor area providing a more accurate indicator of value variations.

The national EPC dataset includes data on about 14.2 million buildings. EPC certificates are required only for newly constructed, sold, or rented dwellings, which results in missing data, especially for older or long-held owner-occupied properties. Most missing values in the analysis are due to properties without an EPC certificate rather than incomplete records.

3.2 Data Integration and Final Dataset Preparation

The VOA council tax band dataset served as the master dataset, onto which the PPD and EPC property attributes were joined. This ensured completeness of the original property records, retaining all properties from the VOA data while integrating supplemental transaction and feature information.

Integration was performed at the property-level using carefully constructed keys. For the PPD dataset, a composite key combining the UPRN with the property and unit number was used to maximise match accuracy, particularly for multi-unit dwellings. Joins were executed within each Local Authority District (LAD) to reduce cross-boundary mismatches before being consolidated nationally. EPC records, often registered at the building rather than unit level, were joined using only UPRN. This localised joining approach ensured both precision and completeness across sources.

Following integration, the combined dataset contained approximately 22.3 million unique properties, corresponding to about 90 percent of chargeable dwellings in England. This coverage differs somewhat from the VOA's published total of 24.9 million chargeable dwellings, with remaining gaps likely reflecting timing differences and records withheld from the open data release. [See Figure 3.11 in Appendix 2.] Notably there is a higher percentage of missing dwellings in the higher bands. While this is namely due to the smaller population of high band dwellings, it also signals that the VOA cleaned their open data and that there is more uncertainty about high-value property records. [See Figure 3.12 in Appendix 2.] Because the PPD dataset includes multiple transactions per property, the integrated dataset expands to roughly 33.0 million rows. This duplication is intentional; it preserves repeat sales and temporal market activity, which are essential for calibrating value models.

Overall, the integration process yields a comprehensive and representative dataset of England's housing stock, combining structural attributes, historical valuations, and observed sale prices. The following section summarises the resulting data completeness and key descriptive characteristics.

3.3 Summary Statistics and Data Quality

Still, the final integrated dataset exhibits significant data sparsity, particularly with respect to transaction prices and EPC attributes. Approximately half of all dwellings lack a recorded sale since 1995, and around one third are missing EPC records. At the individual feature level, roughly two fifths of EPC-related fields are null, reflecting cases where certificates contain only partial information. Detailed summary statistics are shown below in Table 3.1, and Table 3.2 shows the counts of unique authorities per geographic area in our applied dataset. In Appendix 2, Figure 3.16 shows the count of missing values per property feature prior to imputation. (It also shows post-imputation counts and includes engineered features, which will be discussed in the following section.) [Alternatively, refer to Figure 3.1 in the Methodology section for a visual of pre-imputation missing data.] Finally, the price paid trends are captured in a decomposition chart, Figure 3.15, which provides additional insights into seasonality, trends and randomness.

Table 3.1: Initial Summary Statistics after Filtering for Features (excluding Historic Sale Price)

Feature	Min	1st Quartile	Mean	Median	3rd Quartile	Max	Standard Deviation
Current Energy Efficiency	1.000	58.000	65.364	67.000	74.000	991.000	13.154
Number Habitable Rooms	0.000	3.000	4.337	4.000	5.000	137.000	1.772
Total Floor Area	0.010	62.000	88.925	79.000	101.000	47,016.000	53.980
LSOA Deprivation Score	0.541	9.705	20.731	16.923	27.884	92.735	14.622

** Latitude and longitude are also not shown but summary statistics are not relevant.*

Feature	Mode
Built Form	Semi-Detached
Construction Age Band	1950 to 1966
Duration	Freehold
New Build	No
Property Type	House
Tenure	Owner-Occupied

Table 3.2: Count of Distinct Values by Geographic Clusters

Geography	#
Local Authority District (LAD)	309
Middle Super Output Area (MSOA)	6,791
Lower Super Output Area (LSOA)	32,841
Output Area (OA)	170,039

In summary, the datasets and cleaning methodology outlined provide a robust foundation for assessing council tax system efficacy, evaluating property valuation accuracy, and examining the distributional implications of current versus updated property valuations across England. However, they require substantial imputation and transformation to effectively construct price estimation models.

4 Methodology

To evaluate the distributional effects of Council Tax reform, an empirical framework is developed that simulates a range of counterfactual tax systems using imputation and machine learning techniques. Each counterfactual is implemented as a pseudo-simulation in which properties are reassessed using updated valuations and then reassigned under alternative banding structures or tax schedules. The effects of each reform are quantified by comparing simulated Council Tax liabilities to those under the current system at both the individual property-level and the Local Authority District (LAD). This allows for the identification of “winners” and “losers” under each policy design, with outcomes further analysed by geographic location, local deprivation and income levels, and aggregate impacts on household liabilities. The role of Council Tax Support (CTS) is also considered, both under its current structure and under scenarios in which its redistributive effects are incorporated directly into the tax system.

The counterfactual scenarios are designed to represent a range of plausible policy options. Some reflect existing or proposed reforms in Scotland and Wales, while others draw on alternative property tax systems observed internationally. All scenarios assume a full revaluation of properties to contemporary market prices and

differ only in how tax liabilities are structured following this revaluation. This design allows the analysis to isolate the effects of structural reform from those of updating the tax base. The counterfactuals can be grouped into five broad categories: revaluation only, reweighted multipliers, band structure reforms, combined band and multiplier reforms, and alternative tax systems.

To generate and evaluate the scenarios, a modeling pipeline is constructed, which consists of four stages:

1. **Feature Construction and Imputation:** Spatial and temporal features are engineered to capture local housing market structure, and missing property attributes are imputed using a matrix completion approach to produce a complete dataset for all 22.3 million dwellings.
2. **Contemporary Property Valuation Model:** Contemporary property values (as of December 2024) are estimated using a geospatial Random Forest-based automated valuation model (AVM) captures both structural and spatial determinants of housing prices.
3. **Model Validation:** The predictive performance of the valuation model is assessed using out-of-sample validation metrics to ensure that estimated values provide a reliable basis for simulation.
4. **Counterfactual Simulation:** Counterfactual tax systems are implemented by reassigning properties to new bands or applying alternative tax schedules, and the resulting liabilities are compared to those under the current system.

Two features of this framework are particularly important for interpretation. First, all counterfactuals are evaluated under a common valuation baseline, ensuring that differences across scenarios reflect changes in tax structure rather than differences in underlying property values. Second, the simulations are conducted under a nationally revenue-neutral constraint, meaning that total tax revenue is held constant and changes in liabilities reflect redistribution across properties. Together, these design choices allow the analysis to focus on the distributional implications of reform and to identify the mechanisms through which equity gains are achieved. Each component of the framework is discussed in detail in the sections that follow.

4.1 Feature Construction and Imputation

A central challenge in constructing a property-level dataset for this analysis is the incomplete coverage of property characteristics. Because many of these attributes are drawn from EPC data, which is not universally required, substantial gaps remain in the feature set. While the extent of missingness varies by variable, most features are observed for only around two-thirds of dwellings.

To address this, the data preparation process combines feature construction with a structured imputation strategy. Spatial and temporal features are first engineered to capture local housing market conditions and provide contextual information for each property. We then use these features, alongside observed property characteristics, within a multivariate imputation framework to estimate the remaining missing values. Together, these steps produce a complete and internally consistent dataset suitable for valuation modeling and counterfactual simulation.

Feature Engineering for Spatial and Temporal Variation

A critical preparatory step is to create features that capture spatial and temporal patterns in housing values, so that the valuation model can learn local price dynamics and long-term trends. At the highest level, separate models are trained for each Local Authority District (309 across England) to ensure that broad regional differences in housing markets are respected. Within each LAD, additional engineered features are introduced to incorporate finer geographic detail and time-adjusted pricing, as follows:

1. **MSOA-Level Target Encoder:** This feature reflects the mean sale price of properties within each MSOA, calculated using transactions from January 2024 onward. Per MSOA, there is an average of 3,284 dwellings, offering a valuable intermediate resolution between district-level trends and neighborhood-

level variation. To mitigate the impact of outliers, the 1st and 99th percentiles are removed.³⁵ This encoding reflects localised expected price levels while dampening noise from atypical transactions.

2. **Neighborhood Level Coordinates:** To capture fine-grained spatial variation, latitude and longitude are derived from the centroid (with ~6 decimal places precision) of the Output Area. Given that an OA represents the smallest census geographic unit (around 131 dwellings on average), properties are often largely homogenous as they often include a single neighborhood or housing development. By including coordinate features, the model can capture micro-location effects and spatial clustering of property values at a granular level.
3. **Baseline Inflation-Adjusted LAD-Level Price:** Each historic sale price is adjusted to December 2024 levels using a LAD-specific centralised moving average (CMA). The CMA is computed over a five-month centered window where sufficient observations exist (two months prior to and after the transaction date), with a fallback to national trends where necessary. This adjustment ensures comparability across transactions by removing market-wide price drift. Formally, the adjustment is calculated as:

$$\text{adjusted price}_i = \hat{P}_i = p_i \times \frac{CMA_{\text{Dec 2024}}^d}{CMA_{t_i}^d}$$

, where p_i = the historic sales price

and t_i is the truncated transaction month

and CMA^d is centralised moving average in LAD d

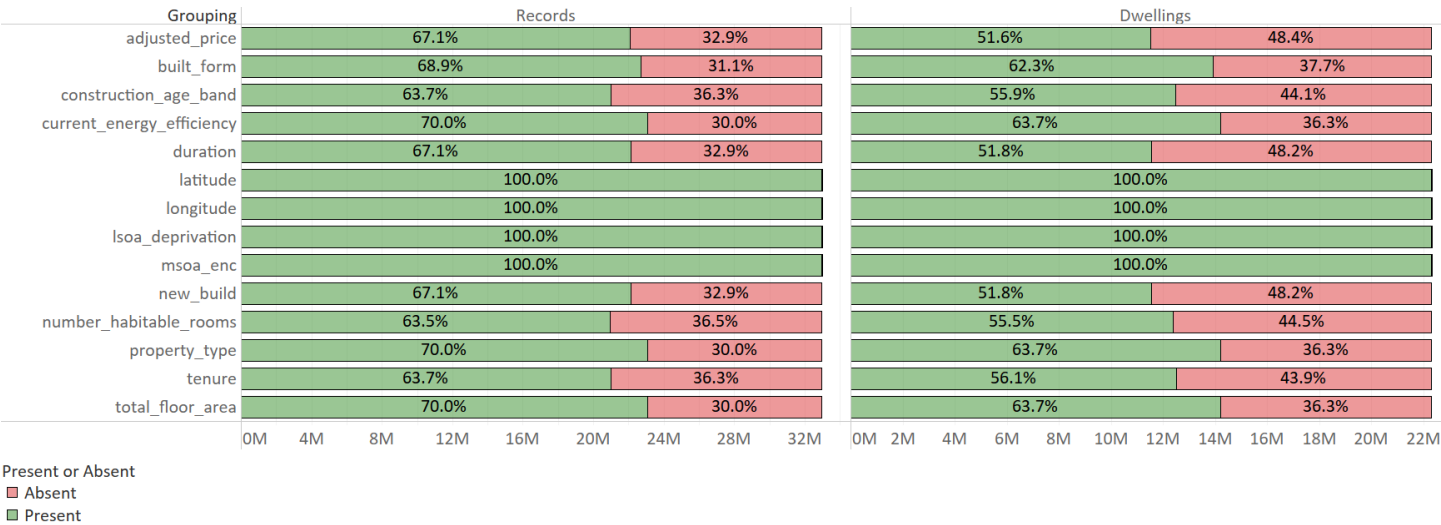
³⁵ Some minor clean-up was also conducted to improve data quality. For example, transactions with implausibly low values (those under £10,000 for Band A or below £25,000 for the other bands likely reflect non-arm's-length transfers or reporting errors and are excluded from price estimation. These records are maintained but the sale price is removed, so that price estimation can occur devoid of the influence of the sale price data point(s). This impacts rough 0.3% of records. Furthermore, while we keep records for properties with multiple sales to enhance trends and estimation, if – after the low values are removed – property records exist both with and without a transaction, the record with a blank sale price is dropped. Similarly, if two or more records exists where neither has a historic sale price, only one record (the most recent) is maintained. This also results in about 0.3% of records being dropped from the dataset.

These transformations enrich the dataset with spatial and temporal context, enabling the valuation model to capture variation in house prices across multiple geographic scales while accounting for both relative price changes and current market levels. As the adjusted price variable already incorporates temporal dynamics, neither the raw sale price nor time since sale are included as direct inputs in the model.

Completion of Property Feature Matrix

With the additional, complete features (except for Adjusted Price, which will only be present if the dwelling sold since 1995), the remaining categorical and numeric features are ready to be estimated. [See Figure 3.1 below for the volume of data points that require imputation at this stage.]

Figure 3.1: Present vs Absent Records and Dwellings Counts Prior to Imputation



Note: This chart illustrates the model inputs prior to imputation. The red portion of the stack bar represents nulls. The green represents present datapoints. Results are summarised by records and unique dwellings.

Before model-based imputation is applied, fine-grained spatial information is used to resolve straightforward cases of missingness. Specifically, a check for feature-level singularity is performed at the Output Area (OA) level. If an OA contains both observed and missing values for a categorical feature, and all observed values are identical, it is assumed that the remaining properties within that OA are homogeneous and missing

values are filled accordingly. This step is particularly relevant for attributes that tend to be uniform within small spatial clusters, such as new build status or tenure.

In aggregate, this deterministic OA-level procedure directly resolves missing values for approximately 5 million properties (around 16% of the dataset). Its impact is concentrated in a subset of categorical variables, accounting for roughly 43.5% of missing values in “new build” status and 36.8% in “duration”, with a smaller but still meaningful effect for “property type”. In contrast, its contribution to other variables is minimal, reflecting greater within-area heterogeneity. An audit of 100 randomly sampled properties suggests that this homogeneity assumption holds in approximately 94% of cases, supporting the use of this approach as a first-stage imputation step prior to model-based methods.

Next, remaining missing values are estimated using a multivariate imputation by chained equations (MICE) approach. As a pre-step, the categorical attributes (new build status, duration, property type, built form, construction age band, and tenure) are label-encoded into numeric form. Converting these categories to integer codes allows us to include them in numerical modeling and imputation processes. Therefore, the categorical attributes are imputed alongside the four numeric features (current energy efficiency score, total floor area, the number habitable rooms, and the LSOA-level deprivation score).

To reserve geographic specificity, this imputation is performed separately within each Local Authority District, so that each model only draws relationships from properties in the same local housing market. The IterativeImputer implementation (from scikit-learn), which models each incomplete feature as a function of all the others in an iterative looping fashion, is used (van Buuren & Groothuis-Oudshoorn, 2011).³⁶ Each of the six

³⁶ Unlike MissForest, which separates imputation by variable type, the MICE approach used here imputes categorical and numeric features jointly by temporarily transforming categorical fields into integer codes. MissForest uses regression forests for numeric fields and classification forests for categorical fields, evaluating convergence via rank correlation and stationary rate, respectively. While MissForest was initially considered, the transition to IterativeImputer was made due to the deprecation of stable Python packages

categorical features and the four numeric features (those with missing values) are each treated as a target variable, as they are sequentially imputed. At each step, the algorithm uses the current known values of all other features to fit a regression model and predict the missing values for the target feature. This approach uses a Bayesian ridge regression as the estimator for these conditional models, which introduces regularization to prevent overfitting given the potentially complex and collinear feature space (van Buuren & Groothuis-Oudshoorn, 2011). The fully observed auxiliary variables, namely longitude and latitude, the MSOA-level price index, the LAD-level inflation-adjusted price, and the local deprivation score are included as additional predictors in these regressions. (They are not imputed themselves since they have no missing values.) The imputer cycles through all incomplete features multiple times, updating the estimates of missing entries with each iteration, until convergence criteria are met or a fixed number of iterations is reached. This procedure yields a single completed dataset where all previously missing entries have been filled with plausible values consistent with the learned relationships in the data.

Formally, for features $X_1, \dots, X_p$, the algorithm iteratively fits:

$$X_j^t = f_j(X_{-j}^t)$$

, where j = is the feature currently being imputed

and X_{-j}^t = the current value for all other features in iteration t

Prediction from f_j are used to update the missing data points in X_j . The sequence $j = \{1, \dots, p\}$ is repeated for $t = \{1, \dots, T\}$. The process yields a single complete dataset that reflects joint feature dependencies.³⁷

supporting MissForest. The unified imputation in MICE simplifies integration and preserves inter-variable relationships across all feature types.

³⁷ Generally, MICE will produce multiple imputed datasets to reflect uncertainty, but the single completed matrix of most likely outcomes is used.

By using the MICE algorithm for matrix completion, we leverage the joint information in the dataset rather than relying on simplistic fills. This approach offers several advantages over simpler imputation strategies like mean substitution or single-variable interpolation. Because each feature is imputed by modeling its conditional dependency on other features, the method inherently accounts for the nonlinear relationships present in real housing data. For example, a property's floor area and energy efficiency rating are all interrelated; the iterative multivariate approach uses these relationships so that the imputed values make sense in combination, rather than treating each variable in isolation. The use of Bayesian ridge regression further helps to stabilise the imputations by shrinking extreme predictions, which is valuable in sparse data contexts. Moreover, performing the imputation within each LAD preserves locality; the model for imputing missing values in a rural district is not distorted by data from an unrelated urban market, for instance. The inclusion of the engineered geographic and temporal features (MSOA price averages, adjusted sale prices, and coordinates) as predictors means that the imputation is informed by a property's neighborhood context and the overall market trend, which helps maintain important spatial and temporal patterns in the completed dataset.

While the imputation procedure is designed to leverage both spatial structure and multivariate relationships, it is important to characterise the extent and nature of missingness in the dataset. Across the retained feature set, approximately 30 percent of values are missing prior to imputation, though this varies by attribute. In most cases, missingness is not concentrated across entire records but rather occurs at the feature level, with many properties missing only a subset of attributes. This pattern reflects the underlying data-generating process, particularly the incomplete coverage of EPC records, rather than systematic absence of information across specific types of properties.

The imputation strategy therefore proceeds in stages. First, a deterministic, spatially localised approach is applied at the Output Area (OA) level, where missing categorical values are filled when all observed values within the OA are identical. This “singularity” condition allows a portion of missing values to be resolved using highly

local information, without reliance on statistical modeling. This step captures cases where properties are likely to be structurally homogeneous, such as within a single housing development. The remaining missing values are then addressed using the multivariate MICE framework, which incorporates both cross-variable relationships and spatial context through the engineered features described above. As a result, the final imputed dataset reflects a combination of local deterministic completion and model-based estimation.

Despite these safeguards, imputation introduces potential sources of bias that must be considered when interpreting results. First, where missingness is not fully random, the imputed values may reflect the characteristics of observed properties rather than the true underlying distribution. Second, model-based imputation may attenuate extreme values, particularly for properties that are outliers within their local area, as predictions are partially “shrunk” toward typical observations. This is especially relevant for high-value or atypical properties, where both feature sparsity and valuation uncertainty are greater.

To assess the impact of imputation on the dataset, summary distributions of both categorical and numeric variables are compared before and after imputation, using only observations with originally observed values as a benchmark. These comparisons indicate that the overall distributional structure of the data is largely preserved, with only minor smoothing effects observed in the tails of some variables. While this does not eliminate all potential bias, it suggests that the imputation procedure maintains the key statistical properties of the dataset and provides a sufficiently robust foundation for subsequent valuation and policy simulation.

Taken together, this staged imputation approach – combining local deterministic completion with multivariate estimation – produces a spatially coherent and internally consistent set of property attributes. This cleaned and enhanced dataset underpins the subsequent analysis, ensuring that when we simulate alternative Council Tax scenarios, the comparisons to the current system are based on accurate and internally consistent information about each property’s characteristics and value.

4.2 Contemporary Property Price Estimation using a Geospatial Random Forest Model

With a fully imputed dataset of property characteristics, the next objective is to estimate the contemporary market value of all available residential properties in England. This is framed as a supervised learning problem, where the aim is to generate accurate out-of-sample predictions of property values rather than to estimate structural relationships between individual attributes and prices.³⁸ For this estimation, a geospatial Random Forest (GSRF) model is employed. Random Forest is an ensemble learning method that constructs multiple decision trees using bootstrap samples of the data and random subsets of predictors at each split, before averaging their predictions to improve accuracy and reduce variance ((Breiman, 2001; Ho T. K., 1995; Liaw & Wiene, 2002).

The objective of the model is explicitly predictive rather than structural. Accordingly, the focus is on generating accurate price estimates rather than interpreting causal effects of individual covariates (Shmueli, 2010). This aligns with the approach taken in related Council Tax reform studies, such as *Revaluation and Reform: Bringing Council Tax in England into the 21st Century* by Adam et al. (2020) and is in-line with the role of AVMs to construct actual estimates at the property-level.

Random Forests are particularly well-suited to this task due to their ability to capture complex, nonlinear relationships and interactions across heterogeneous property characteristics, especially in the presence of spatial variation. Compared to traditional hedonic regression models, which impose a parametric structure, RFs allow the relationship between features and prices to be learned directly from the data, making them effective in large-scale property valuation contexts.^{39,40} By making minimal assumptions about functional form, RF is able to

³⁸ A neural network model was also developed but produced unreliable results. With better hyperparameter tuning, this could prove to be a valuable alternative. In Wang and Wu (2018) artificial neural networks were tested for price prediction strategies and were demonstrated to be promising. Still, Awonaike (2022) acknowledges that real world application to property valuation have been limited (Wu & Wang, 2018; Awonaike, 2022).

³⁹ RF is a data-driven, non-parametric model; instead of specifying a parametric equation for prices, it learns the relationship from data by recursive partitioning.

⁴⁰ Random Forest builds on the method of “bagging,” meaning that each decision tree is training using a distinct random subset of both data and features, and at every split a random subset of predictor variables is considered. This reduces correlation among trees (Breiman,

capture complex, nonlinear relationships. Property valuations involve several heterogeneous properties with nonlinear interactions. For example, the complex relationship between location and the size of a property varies widely by location. Unlike a traditional hedonic regression that assumes a linear combination of features, a random forest can naturally model nonlinear and interaction effects without manual feature engineering. While features have been imputed to enhance the accuracy, RF is relatively robust to outliers and missing data, and it can handle large counts of variables (Liaw & Wiene, 2002). While the property data has been heavily cleaned for obvious outliers and illogical data, noisy data is common in property statistics and likely persist after imputation.

Empirical evidence supports the use of Random Forest models in mass appraisal settings, often outperforming traditional valuation models. For example, a Random Forest model predicting apartment prices in Seoul achieved an average prediction error of only ~5.5%, compared to ~20% for a comparable OLS hedonic regression; furthermore, 72% of the RF's predictions fell within 5% of true market prices (versus only 17.5% for OLS) (Hong, Choi, & Kim, 2020). Similarly, Čeh et al. (2018) showed that RF predicted apartment values more accurately than multiple regression, especially in complex urban environments, by better detecting variability in prices across locations (Čeh, Kilibarda, Lisec, & Bajat, 2018). The ability of RFs to automatically model nonlinear price trends and interaction effects therefore enables higher predictive power and adaptability and gives them a significant advantage in AVMs.

Prior to price estimation, several data transformations are applied. First, the dataset is partitioned into two segments based on the availability of transaction history. The first segment contains dwellings that have at least

2001). This random subspace selection introduces variation across trees and enhances the model's robustness (Breiman, 2001; Ho T. K., 1995). Generally,

$$\hat{y}(x) = \frac{1}{T} \sum_{t=1}^T f^t(x)$$

, where T = the number of trees and $f^t(x)$ = the prediction of the t -th decision tree. Averaging numerous such trees reduces prediction variance and helps prevent overfitting (Liaw & Wiene, 2002; Breiman, 2001).

one recorded sale (since 1995). The second segment contains those with no recorded sale price in that period. Second, the six categorical variables are one-hot encoded (OHE) into binary indicator variables. Unlike the approach taken for the imputation, this expands each categorical feature into multiple 0/1 columns (one per category level) so that the Random Forest can treat each category independently. Formally:

$$x_{ij}^{cat} \in \{0,1\} \Rightarrow x_{ij}^{cat} = 1$$

For this study, the GSRF is used to construct an “adjusted price,” which is an estimated value of each property in December 2024. As about 47% of properties have multiple sales and thus multiple records prior to the model, the number of records can be expressed as follows:

$$n_i = (1_{s_i=0} + s_i) \times 1_{s_i=1}$$

, where n_i = number of records for dwelling i

and s_i = number of sales for dwelling i

$$N = \sum_{i=1}^{|D|} n_i$$

, where N = total number of records (observations)

and D = the set of all dwelling such that $d_i \in D$

Letting P be the number of training features, the training data can be represented as a feature matrix $X \in \mathbb{R}^{N \times P}$, and the target vector can be represented as $y \in \mathbb{R}^N$. Each record i 's feature vector, $x_i = [x_{i1}, x_{i2}, \dots, x_{iP}]$, includes the following:

1. The inflation-adjusted sale price (adjusted_price)
2. The MSOA encode recent average sale price (msoa_enc)
- 3-4. OA-level longitude and latitude (longitude and latitude)
5. Total floor area in square meters (total_floor_area)

6. Number of habitable rooms (number_habitable_rooms)
7. Current energy efficiency store (current_energy_efficiency)
8. LSOA overall deprivation score (lsoa_deprivation_score)
- 9-10. New Build OHE fields (new_build_no and new_build_yes)
- 11-12. Duration OHE fields (freehold and leasehold)
- 13-17. Property Type OHE fields (bungalow, flat, house, maisonette, and park_home)
- 18-23. Built Form OHE fields (detached, enclosed_end-terrace, enclosed_mid-terrace, end-terrace, mid-terrace, and semi-detached)
- 24-34. Construct Age-band OHE fields (<1900, 1900 to 1930, 1930 to 1949, 1950 to 1966, 1967 to 1975, 1976 to 1982, 1983 to 1990, 1991 to 1995, 1996 to 2002, 2003 to 2006, and >2006)
- 35-37. Tenure OHE fields (owner-occupied, rental-private, and rental-social)

The feature matrix is thus $X \in \mathbb{R}^{N \times 37}$. The trained model $\hat{f}$ is a function that maps the feature vector to the contemporary price $\hat{f}: \mathbb{R}^P \rightarrow \mathbb{R}$.

The Random Forest is trained using 100 regression trees, each constructed from a bootstrap sample of approximately two-thirds of the available observations.⁴¹ At each split, a random subset of predictors is evaluated, introducing variation across trees and improving robustness. Trees are grown until a minimum leaf size of five observations is reached, balancing model flexibility with overfitting control. No pruning is applied, with overfitting mitigated through ensemble averaging (Breiman, 2001). Formally, the Random Forest model consists of an ensemble of decision trees, where predictions are generated by averaging across trees:

$$\hat{y}(x) = \frac{1}{100} \sum_{t=1}^{100} f^t(x)$$

⁴¹ A test to see if prediction changed largely with 200 independent trees was performed. On average, estimation changed only by 0.9% and were symmetrical about the mean implying that there is only a margin, potential gain from increasing the number of trees (at the cost of more memory consumption) beyond the 100 default.

, where T = total number of trees

and $f^t(x)$ = the prediction from the t^{th} tree

(Breiman, 2001)

Separate models are estimated for each Local Authority District (LAD), allowing the model to capture region-specific housing market dynamics. Training is conducted using only records with observed transaction prices. Once trained, each LAD-level model is applied to estimate contemporary values for all properties within that district, including those without observed sale prices. The resulting output is an “adjusted price,” representing the estimated market value of each property as of December 2024. These estimates form the basis for the subsequent counterfactual tax simulations.

4.3 Price Estimation Model Validation

A key advantage of Random Forest models is their ability to provide internal validation through out-of-bag (OOB) samples. Because each tree is trained on a bootstrap sample (roughly 63% of the data), about 37% of the training observations are left out (not used) in that tree’s construction (Breiman, 2001). For each training property i , we can obtain an out-of-bag prediction $\tilde{y}_i$ by averaging the predictions of all trees for which i was not in the training sample. This provides an internal cross-validation mechanism without requiring a separate validation dataset.

Model performance is evaluated using three standard metrics based on OOB predictions. The first is the coefficient of determination (R^2), defined as:

$$R_{OOB}^2 = 1 - \frac{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

, where y_i = inflation adjusted price of record i

and $\tilde{y}_i$ = OOB prediction price

and $\bar{y}$ = is the mean of y in the training data

The R_{OOB}^2 represents the fraction of variance in the training prices explained by the model's OOB predictions, which is effectively an unbiased estimate of the model's goodness-of-fit. Thus, the value of the R_{OOB}^2 represents the percentage of the variation in prices that is captured by the model using “out-of-bag” data. Values closer to 1 represent more predictive performance (Breiman, 2001).

In addition to R^2 , two complementary error-based metrics are used. First, the MAE measures the average absolute difference between actual prices (y_i) and their predicted values ($\tilde{y}_i$), across all n samples. It is generally more interpretable as the average absolute deviation of predicted price from actual price. Formally:

$$MAE_{OOB} = \frac{1}{n} \times \sum_{i=1}^n |y_i - \tilde{y}_i|$$

A low RMSE and MAE alongside a high OOB R_{OOB}^2 suggest the model is capturing the pricing patterns well without overfitting.

The second is the Root Mean Squared Error (RMSE). This is the square root of the average squared differences between actual prices (y_i) and OOB predictions ($\tilde{y}_i$), calculated across all n training samples. Essentially, large errors are penalised more heavily. Formally...

$$RMSE_{OOB} = \sqrt{\frac{1}{n} \times \sum_{i=1}^n (y_i - \tilde{y}_i)^2}$$

The OOB measures showed overall stable performance with meaningful variation at the LAD level namely driven by only 15 local authority districts. The record-weighted national average R_{OOB}^2 was roughly 0.558. 186 LADs outperforming the mean and about one-third had a $R_{OOB}^2 \geq 0.70$. The MAE_{OOB} and $RMSE_{OOB}$ exhibited similar skewness, with average values of £48,795 and £239,038 respectively. Out of 309 LADs, 203 had a MAE

above the mean and 218 had an RMSE above the mean. These findings show that although some districts have higher explanatory power than the mean, most have absolute and squared errors exceeding national averages, indicating that error distributions are affected by local conditions.

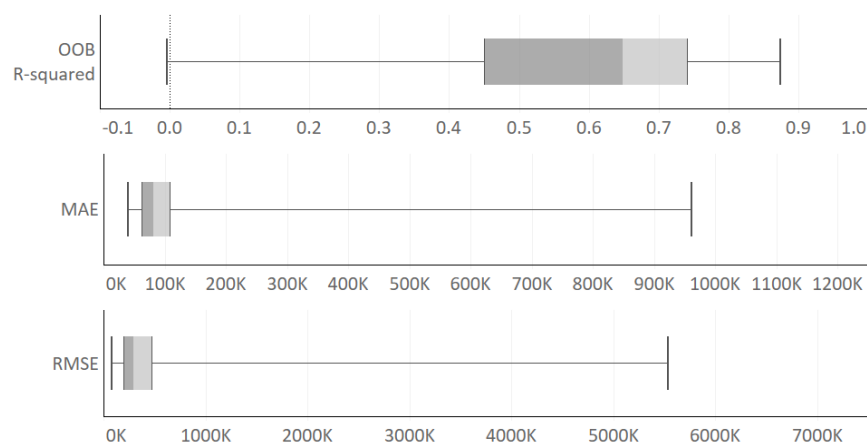
Overall, the average values align with initial expectations for property price modelling at the LAD level. Variation in housing markets and property values can result in higher RMSE values, which respond to extreme data points. Outlier values observed in approximately 20 LADs appear to be influenced by a pronounced right-tail in property price distribution. [See Figure 3.14 in Appendix B.] The greater variance found in districts with unusually high-value properties explains much of the spread, while the weighted national averages remain stable, indicating that the model performs consistently across most of England.^{42,43}

⁴² Future improvements could be achieved by training a model on cleaner PPD data that removes outliers on the high end – especially if the highest value properties are categorized into a single tax liability anyway. Additionally, explicitly introducing spatial autocorrelation controls or adopting hedonic adjustment approaches that down-weight the influence of outlier transactions may be helpful.

⁴³ An alternative contemporary price prediction model was also trained in which the adjusted_price low log-transformed prior to model fitting. Under this framework, the final predictions were re-exponential using a smearing estimator to account for retransformation bias (Duan, 1981). The resulting values were very similar, as shown below. As much of the variance is already captured by structural and spatial predictors, the marginal differences again likely stem from the smaller population of very high-value properties. While important, the issue is constrained to a relatively small fraction of the overall housing stock.

Model		R^2_{OOB}	MAE_{OOB}	$RMSE_{OOB}$
Non-Log (Reported)		0.558	£48,795	£239,038
Log-transformed	Adjusted	0.510	£48,450	£253,054
Price				

Figure 3.2: OOB Measure Results from the Contemporary Price Prediction Model



Note: The box-and-whisker plot represents the average out-of-box R^2 , MAE , and $RMSE$ for the housing price prediction model per LAD. The whiskers represent the most extreme LADs with the center of the box representing the median value.

4.4 Counterfactual Simulation

Having estimated contemporary property values for every dwelling as of December 2024, the next step is to simulate a range of Council Tax counterfactuals. These simulations examine how alternative tax designs redistribute liabilities relative to the current system, with a particular focus on equity outcomes.

Three defining assumptions underpin all counterfactual scenarios in this analysis. First, each scenario begins with a full revaluation of the property tax base, ensuring that tax liabilities reflect contemporary market values rather than historical assessments. Second, all scenarios are modeled as nationally revenue-neutral, meaning that total tax revenue is held constant. Third, unless otherwise stated, redistribution occurs across the country as a whole rather than within individual local authorities. Together, these assumptions provide a consistent

framework for isolating the effects of structural reform and evaluating how different tax designs alter the distribution of liabilities.^{44,45}

The mechanics of revenue neutrality are central to the interpretation of results. Across all reform categories, outcomes are driven by how tax rates are adjusted across the property value distribution. Three factors are particularly important. First, the magnitude of increases applied to higher-value properties determines the total resources available for redistribution. Second, the breadth of these increases – whether concentrated in the top band or applied across multiple upper bands – affects how widely the burden is shared. Third, the structure of adjustments at the lower end determines how savings are allocated, whether proportionally across all properties or more directly targeted toward middle- or lower-value dwellings.

Because lower-value bands contain the majority of properties, increases applied to a relatively small number of high-value dwellings typically translate into modest per-household reductions unless redistribution is explicitly targeted. This interaction between the concentration of tax increases and the distribution of resulting benefits underpins all revenue-neutral scenarios and is central to understanding the equity implications of the reforms considered.

Broadly, the counterfactuals fall into five categories of reform:

⁴⁴ The simulations performed and counterfactuals constructed in this paper illustrate a range of parameterized options, with particular emphasis on those that are revenue neutral and nationally redistributed. The post-imputation processes and property price estimation simulations utilize a Python function designed to accommodate both revenue-constrained and unconstrained models at either the Local Authority District (LAD) or national scale. Furthermore, parameters such as the number of bands, multiplier adjustments, and dwelling distribution per band may be modified as needed.

⁴⁵ The assumption of national redistribution represents a departure from the current institutional structure of Council Tax, under which local authorities set tax rates to meet locally determined funding requirements. In practice, this would imply a more centrally coordinated system of redistribution, with local funding differences accommodated through mechanisms such as intergovernmental transfers. This assumption is necessary to evaluate the full extent of distributional inequities in the current system. In particular, the most significant source of inequity arises from spatial disparities driven by uneven property price growth since the early 1990s. Reforms that operate solely within local authority boundaries cannot address these imbalances, as they preserve the relative distribution of tax bases across regions. As such, national redistribution provides a useful benchmark for assessing the potential equity gains from revaluation and structural reform.

- **Revaluation Only** (Category 1): Updates property values while keeping the band structure and multipliers unchanged.
- **Reweight Multipliers** (Category 2): Retain the eight-band structure but modify the band multipliers to make the tax more progressive with respect to value.
- **Band Structure Reforms** (Category 3): Expands or restructures the number of tax bands to improve horizontal equity, while changing multipliers to account for the new band counts.
- **Band Structure Reforms with Value Reweight Multipliers** (Category 4): Combines band expansion with multiplier reweighting to better align liabilities with property values.
- **Alternative Tax Systems** (Category 5): Replaces the band system entirely with value-based taxation, either proportional or progressive, and explores alternative relief mechanisms.

A consistent analytical framework is used to assess and compare the reforms. Distributional outcomes are evaluated by identifying the proportion of dwellings experiencing increases, decreases, or no change in tax liability. Equity is assessed through changes in the relationship between effective tax rates and property values, as well as their correlation with household income and deprivation indicators, capturing shifts in vertical fairness. In addition, rate–value equality is used to assess how effective tax rates vary across the value distribution, indicating whether the system becomes more or less regressive under each reform.

Together, these measures provide a consistent basis for evaluating how alternative tax designs redistribute the burden across the property value spectrum, local authorities, and household groups, while maintaining constant overall funding. This framework allows each counterfactual to be assessed using a common set of metrics, ensuring that differences in outcomes reflect the structure of the reform rather than differences in measurement.

Category 1: Revaluation Only

This category isolates the effect of revaluation alone, holding the structure of the tax system constant. The first category contains only the revaluation scenario, counterfactual 1.1.⁴⁶ For this study, it serves as a benchmark rather than a reform proposal independently. It, however, does represent an alternative system, and revaluation alone represents the most significant part of any counterfactual. This simulation holds both the number of bands and the distribution of dwellings across those bands constant. Using the estimated 2024 property values produced by the random forest model, all dwellings are rank-ordered at the national level and reassigned into the eight existing bands so that the share of dwellings in each band matches today's national distribution. After dwellings are assigned, new band value ranges are determined using the empirical distribution. Each band encompasses allocated property values, with boundaries set at the midpoint between the maximum of one band and the minimum of the next. Every range starts £0.01 above the previous band's upper limit to maintain continuity; Band A starts at £0.00, and Band H does not have an upper cap. This arrangement mirrors the current band design and adjusts the tax base to reflect contemporary values. The results are shown in Table 3.3.

⁴⁶ In testing, alternative benchmark counterfactuals 1.1B and 1.1C were included to illustrate the implications of local versus national constraints. Under 1.1B, each local authority retains its existing distribution of dwellings by band and maintains revenue neutrality within the council, so revaluation corrects mis-banding only within the local authority. Thus, there is less movement but regional inconsistencies largely persist. Under 1.1C, national band counts are preserved but each council's aggregate liability is held constant, which namely drives differing tax liabilities within like-bands across LADs. Because councils adjust Band D rates annually with little correlation to deprivation or property values, these local constraints preserve the existing regional advantages and disadvantages rather than aligning liabilities with market values. (Figure Z maps the funding imbalances that arise when revenue is constrained nationally rather than locally.) The inherent spatial differences that persist when LAD-level constraints apply obfuscate equity gain measurements. Thus, we focus solely on the current system and a national simple redistribution (1.1A) as benchmarks.

Table 3.3: Estimated Property Price Range vs Current by Band

Band	National Distribution of Dwellings	Current Low (1991 Values)	Current High (1991 Values)	Estimated Low (2014 Values)	Estimated High (2014 Values)	Low Multiple	High Multiple
A	23.50%	£0.00	£40,000.00	£0.00	£186,758.73	1.00	4.79
B	19.70%	£40,000.01	£52,000.00	£186,758.74	£256,806.94	4.79	5.11
C	22.40%	£52,000.01	£68,000.00	£256,806.95	£354,400.27	5.11	5.45
D	16.20%	£68,000.01	£88,000.00	£354,400.28	£465,393.64	5.45	5.65
E	10.20%	£88,000.01	£120,000.00	£465,393.65	£624,860.77	5.65	5.70
F	3.80%	£120,000.01	£160,000.00	£624,860.78	£776,392.50	5.70	5.45
G	3.80%	£160,000.01	£320,000.00	£776,392.51	£1,691,060.83	5.45	6.51
H	0.50%	£320,000.01	∞	£1,691,060.84	∞	6.51	1.00

As with other counterfactuals in this study, the benchmark maintains national revenue neutrality, keeping total council tax revenue unchanged but shifting liabilities between properties. This reduces regional tax rate disparities and shifts liabilities toward previously under-taxed high-value properties. By preserving the current band structure and multipliers, this scenario isolates the effect of revaluation, serving as the baseline for assessing the impact of further reforms.⁴⁷

Category 2: Reweighted Multipliers

The second counterfactual category maintains the existing eight-band structure but alters the relative tax rates (multipliers) assigned to each band. This category examines how changes to the tax schedule alone – holding band definitions constant – affect the distribution of liabilities. Since the bands remain A–H, multipliers are

⁴⁷ Two alternative revaluation exercises were carried out to evaluate the outcomes of using locally constrained band structures. In the first exercise, the number of dwellings per band was fixed at the local authority district (LAD) level, and revenue was held constant locally to maintain LAD budget limits. In the second, national revenue neutrality was maintained while preserving local band distributions. These methods restrict fiscal transfers between authorities and maintain local budgets. However, they reduce the consistency between property values and tax liabilities on a national scale. Because band distributions are defined within each LAD, dwellings with similar market values may be allocated to different bands according to local rankings. This increases spatial variation in effective tax rates and decreases the correlation between property value and tax liability. It also produces a more segmented and less proportional distribution, which complicates cross-area comparisons. As a result, these locally constrained versions are presented only in supplementary analysis and are excluded from the main counterfactuals.

expressed relative to the Band D multiplier of 1.000. The counterfactuals in this category test how alterations to the “tax schedule” modify can improve fairness (as defined by the percentage of the liabilities to the value of the property) without changing the band structure.

Adjusted Upper-Band Multipliers (Scotland) (2.1)

In 2017, Scotland increased the multipliers applied to Bands E–H to enhance progressivity at the upper end of the property value distribution, raising the Band A–H ratio from approximately 3.0 in England to around 3.68. Counterfactual 2.1 applies this revised multiplier schedule to the existing band structure, increasing liabilities for higher-value bands while leaving Bands A–D unchanged. This isolates the effect of a modest increase in progressivity within the current system, without altering band definitions or the distribution of dwellings across bands. The current and Scottish multiplier schedules are shown in Table 3.4.

Table 3.4: Counterfactual 2.1’s Multipliers vs Current

Source	A	B	C	D	E	F	G	H
Current	0.667	0.778	0.889	1.000	1.222	1.444	1.667	2.000
Scotland 2017	0.667	0.778	0.889	1.000	1.310	1.630	1.960	2.450

Enhanced Upper-Band Multipliers (Scotland Purposed) (2.2)

Counterfactual 2.2 extends the approach in 2.1 by applying the higher multiplier schedule proposed by the Scottish Government in 2023, further increasing rates for Bands E–H. These multipliers, reported in *Modelling the Council Tax Freeze in Scotland: A Guide to the Facts and Figures* (University of Strathclyde, 2023), further increase the Band A to Band H ratio to roughly 4.50. This provides a more progressive variant of the existing band system, allowing for greater redistribution from higher-value properties while still preserving current band definitions. The resulting multiplier schedule is shown in Table 3.5.

Table 3.5: Counterfactual 2.2's Multipliers vs Current

Source	A	B	C	D	E	F	G	H
Current	0.667	0.778	0.889	1.000	1.222	1.444	1.667	2.000
Scotland Proposed	0.667	0.778	0.889	1.000	1.410	1.830	2.300	3.000

Band Midpoint Value Multipliers (2.3)

Counterfactual 2.3 applies multipliers that are instead based on the mid-point of each band's property value range, scaling rates in proportion to these values while anchoring Band D at 1.000. This approach ties tax liabilities more directly to the underlying structure of the band system, using the midpoint of each band as a proxy for representative property value.

A notable policy design challenge arises for the highest band (Band H), as it is uncapped and exhibits a highly skewed distribution. While the average value of Band H dwellings is estimated as ~£2.34 million, there are many properties significantly above this point. In fact, 16.7% of Band H dwellings exceed £5m, and the maximum value observed is £156.6 million. Using the true midpoint would place disproportionate weight on extreme high-value properties. To address this, the Band H multiplier is constrained to one-half of a standard deviation above the mean ($\bar{v}_H + 0.5\sigma_H$), limiting the influence of extreme outliers while retaining the overall structure of the band.

Formally, the mid-point of each band is defined as M_b :

$$M_b = \frac{P_b^{low} + P_b^{high}}{2}$$

, where P_b^{low} = lowest property value range for band b

and P_b^{high} = highest property value range for band b

and $P_H^{high} = \bar{v}_H + 0.5\sigma$

Then, the multiplier m_b is the ratio of the mid-point of each band M_b relative to band D, M_D .

$$m_b = \frac{M_b}{M_D}$$

This approach produces a substantially steeper liability gradient, with Band H liabilities approximately 26 times those of Band A (before CTS), broadly reflecting the underlying ratio of property values. As a result, this counterfactual delivers significant redistribution toward lower-value households while concentrating tax increases at the top of the distribution. The resulting multipliers are shown in Table 3.6.

Table 3.6: Counterfactual 2.3's Estimated Mid-point Values and Multipliers vs Current

Band	Current Multiplier	Estimated Mid-point	Proposed Multiplier
A	0.667	£93,379.37	0.228
B	0.778	£221,782.84	0.541
C	0.889	£305,603.61	0.746
D	1.000	£409,896.96	1.000
E	1.222	£700,626.64	1.330
F	1.444	£777,532.46	1.709
G	1.667	£1,233,726.67	3.010
H	2.000	£2,409,786.21	5.879

Mean Value-based Multipliers (2.4)

Counterfactual 2.4 builds on the approach in 2.3 by deriving multipliers from the mean estimated property value within each band, rather than the midpoint of the band's value range. This anchors the tax schedule to the observed distribution of property values, allowing multipliers to reflect within-band skew.

The mean-value across the dwellings in band b is formally:

$$\bar{v}_b = \frac{\sum_{i \in b} v_i}{n_b}$$

, where v_i = estimated, contemporary value for dwelling i

and n_b = number of dwellings in band b

Then the multipliers for each band m_b are expressed relative to band D:

$$m_b = \frac{\bar{v}_b}{\bar{v}_D}$$

As in 2.3, Band H requires adjustment due to its highly right-skewed distribution. To mitigate this, Band H's mean is computed on the same reduced range as 2.3 counterfactuals, where values above $\bar{v}_H + 0.5\sigma_H$ are assigned the same rate. This preserves the observed H cohort while reducing undue distortions from a small number of very high-value outliers.

By using mean values rather than midpoints, this approach produces a less extreme gradient than 2.3, as it reflects the actual distribution of dwellings within each band. For example, Band A tends to be right-skewed, resulting in a higher average than its midpoint, while Band H is left-skewed relative to its range. The resulting Band A–H ratio is just under 8:1, which is substantially more progressive than the current system, but significantly less steep than the 26:1 ratio in 2.3. Furthermore, this approach retains some advantages of the banding framework, as properties are still grouped within value ranges, providing a buffer against individual valuation error. The resulting multipliers are shown in Table 3.7.

Table 3.7: Counterfactual 2.4's Estimated Average Values and Multipliers vs Current

Band	Current Multiplier	Estimated Avg Value	Proposed Multiplier
A	0.667	£168,181.65	0.416
B	0.778	£243,920.30	0.603
C	0.889	£317,966.84	0.786
D	1.000	£404,757.25	1.000
E	1.222	£499,710.65	1.235
F	1.444	£618,070.10	1.527
G	1.667	£874,485.75	2.161
H	2.000	£1,266,043.02	3.128

Category 3: Band Structure Reforms

The third counterfactual category expands the existing eight-band Council Tax structure by introducing additional bands. The category explores whether increasing the granularity of the banding system can reduce distortions that arise from the current band widths, which have been criticized for creating horizontal inequities. These occur because properties near the top of a band's value range are under-taxed relative to their value, while those near the bottom are over-taxed. As shown in Figure 3.14, contemporary estimated values indicate that property prices within most bands are concentrated toward the lower end of each range, with particularly pronounced left skew in the highest bands. The only exception is Band A, where values are concentrated toward the upper end.

In this category, the primary reform mechanism is to reduce band widths through the addition of new bands. A secondary mechanism is to adjust the tax schedule, similar to Category 2, by applying relatively higher multipliers to new upper bands and relatively lower multipliers to new lower bands. In most cases, these adjustments extend the current multiplier structure rather than fully redefining it, making the reforms more administratively feasible while improving alignment between tax liabilities and underlying property values. As a result, these reforms tend to be less disruptive and achieve more incremental gains in equity than the more structural changes considered in Category 2.

Add Top Band (Wales) (3.1)

Counterfactual 3.1 replicates the approach taken in Wales during the 2005 revaluation, where a ninth band (Band I) was introduced by splitting the existing top band. In effect, Band H was split into H and I with a higher multiplier of 2.333 relative to Band D applied to the new tier. The resulting structure is shown in Table 3.8.

This represents an incremental reform that preserves most of the existing band structure while introducing greater differentiation at the top of the value distribution. Given that Band H exhibits a left-skewed distribution, the reform aims to distinguish more clearly between high-value and very high-value dwellings, addressing the broad range of values currently captured within the top band.

The only deviation that this counterfactual takes from the design of the 2005 Welsh reform is that (given the new valuation and value bands) assumptions were made on how to divide Band H. In short, newly estimated property price range that defines Band G, W_G , is used to define the width of Band H while all other dwellings are assigned to Band I. Formally:

$$W_G = P_G^{high} - P_G^{low}$$

$$P_H^{high} = P_G^{high} + 0.01 + W_G = P_H^{low} + W_G$$

$$P_I^{low} = P_H^{high} + 0.01$$

Using the contemporary estimated prices, W_G is about £1.21 million, so the property values ranges extend as shown in Table 3.8.

Table 3.8: Counterfactual 3.1's New Band Price Ranges, Counts, and Multipliers vs Current

Band	Current Dwellings Count	Current Multiplier	Proposed Dwelling Count	Proposed Resulting Band Range Low	Proposed Resulting Band Range High	Proposed Multiplier
A	5,243,302	0.667	5,243,302	£0.00	£186,758.73	0.667
B	4,386,631	0.778	4,386,631	£186,758.74	£256,806.94	0.778
C	5,005,311	0.889	5,005,311	£256,806.95	£354,400.27	0.889
D	3,605,132	1.000	3,605,132	£354,400.28	£465,393.64	1.000
E	2,276,046	1.222	2,276,046	£465,393.65	£624,860.77	1.222
F	848,246	1.444	848,246	£624,860.78	£776,392.50	1.444
G	837,694	1.667	837,694	£776,392.51	£1,691,060.83	1.667
H	101,266	2.000	72,299	£1,691,060.84	£2,605,729.16	2.000
I			28,967	£2,605,729.17	∞	2.333

The modeled distribution yields a dwelling population ratio between H and I, $m_H:m_I$, of roughly 2:1.

Additionally, $\frac{m_I^{new}}{m_A^{new}} \approx 3.5$, compared to the $\frac{m_H^{orig}}{m_A^{orig}} \approx 3.0$ currently.

Split Upper Bands (3.2)

Counterfactual 3.2 extends the approach in 3.1 by introducing greater granularity among high-value properties through the subdivision of both Bands G and H. Specifically, Band G is split into G1 and G2, and Band H into H1 and H2, resulting in ten total bands. G1 retains the original Band G multiplier (1.667), while G2 adopts the Band H multiplier (2.000). Higher multipliers are then applied to H1 and H2 at 2.333 and 2.667 respectively, as shown in Table 3.9.

This structure reflects previous reform conversations in Scotland, such as the proposal discussed in *A Fairer Council Tax for Scotland*, though different thresholds and parameters were considered (Welsh Government, 2022). Band G is divided into two equal-width segments, with the property value range split exactly at the midpoint. Band H is split using the same method as in 3.1, where the width of the original Band G, W_G , is applied to define the width of Band H, W_H .

$$P_{G_2}^{low} = P_{G}^{low} + \frac{W_G^{orig}}{2}$$

$$P_{H_2}^{low} = P_H^{low} + \frac{W_H^{orig}}{2}$$

The resulting segmentation produces four upper bands with progressively smaller populations, allowing for more targeted taxation of high-value and ultra-high-value properties while limiting impacts on moderately valued dwellings. The full specification is shown in Table 3.9.

Table 3.9: Counterfactual 3.2's New Band Price Ranges, Counts, and Multipliers vs Current

Band	Current Dwellings Count	Current Multiplier	Proposed Band	Proposed Dwelling Count	Proposed Resulting Band Range Low	Proposed Resulting Band Range High	Proposed Multiplier
A	5,243,302	0.667	A	5,243,302	£0.00	£186,758.73	0.667
B	4,386,631	0.778	B	4,386,631	£186,758.74	£256,806.94	0.778
C	5,005,311	0.889	C	5,005,311	£256,806.95	£354,400.27	0.889
D	3,605,132	1.000	D	3,605,132	£354,400.28	£465,393.64	1.000
E	2,276,046	1.222	E	2,276,046	£465,393.65	£624,860.77	1.222
F	848,246	1.444	F	848,246	£624,860.78	£776,392.50	1.444
G	837,694	1.667	G1	691,582	£776,392.51	£1,233,726.67	1.667
H	101,266	2.000	G2	146,112	£1,233,726.68	£1,691,060.83	2.000
			H1	72,299	£1,691,060.84	£2,605,729.16	2.333
			H2	28,967	£2,605,729.17	∞	2.667

Split Lower Bands (3.3)

Counterfactual 3.3 focuses on the lower end of the value distribution by subdividing Band A into two categories, A1 and A2. This addresses concerns regarding the wide range of the lowest band and its impact on lower-value and often more deprived households.

Unlike the upper bands, Band A is split based on dwelling counts due to its zero lower bound and data limitations related to historical sale records for low-value properties.

$$n_{A_1}^{new} = \frac{n_A^{new}}{2}$$

$$n_{A_2}^{new} = n_A^{orig} - n_{A_1}^{new}$$

A2 retains the current Band A multiplier, while A1 assigned a reduced value of 0.500. All other multipliers remain unchanged, as shown in Table 3.10. This represents a targeted and relatively modest reform that increases progressivity at the lower end of the distribution while preserving the overall structure of the system.

Table 3.10: Counterfactual 3.3’s New Band Price Ranges, Counts, and Multipliers vs Current

Band	Current Dwellings Count	Current Multiplier	Proposed Band	Proposed Dwelling Count	Proposed Resulting Band Range Low	Proposed Resulting Band Range High	Proposed Multiplier
A	5,243,302	0.667	A1	2,621,651	£0.00	£142,553.63	0.500
B	4,386,631	0.778	A2	2,621,651	£142,553.64	£186,758.73	0.667
C	5,005,311	0.889	B	4,386,631	£186,758.74	£256,806.94	0.778
D	3,605,132	1.000	C	5,005,311	£256,806.95	£354,400.27	0.889
E	2,276,046	1.222	D	3,605,132	£354,400.28	£465,393.64	1.000
F	848,246	1.444	E	2,276,046	£465,393.65	£624,860.77	1.222
G	837,694	1.667	F	848,246	£624,860.78	£776,392.50	1.444
H	101,266	2.000	G	837,694	£776,392.51	£1,691,060.83	1.667
			H	101,266	£1,691,060.84	∞	2.000

Full Band Splitting (3.4)

Counterfactual 3.4 is the most extensive Category 3 reform, applying band subdivision across the entire value distribution, rather than focusing solely on the upper or lower extremes. This approach addresses variation within all bands, not just those at the extremes, allowing for smoother transitions across the property value spectrum and improved vertical equity.

Different bands require different splitting methods. They are as follows:

1. **Band A** → {**A1**, **A2**}: Uses the same dwelling-count methodology as in 3.3, where the dwelling counts are halved between the groups. (See 3.3 for the rationale for using this approach.) A lower multiplier for A1 is assigned, and A2 receives the former A multiplier.

$$m_{A_1} = 0.500$$

$$m_{A_2} = 0.667$$

2. **Bands B-G** → {**B1**, **B2**, ..., **G2**}: Each band is split into two based on creating two equivalent property value ranges for the “1” and “2” segmentations. Formally, for $b \in \{B, C, \dots, G\}$ with range $[P_{b,high}, P_{b,low}]$:

$$P_{b_1}^{high} = P_b^{low} + \frac{P_b^{high} - P_b^{low}}{2}$$

$$P_{b_2}^{low} = P_{b_1}^{high} + 0.01$$

The lower sub-band receives a slightly reduced multiplier, while the upper sub-band receives a slightly increased multiplier. [See [Table 3.11.](#)]

3. **Band H** $\rightarrow \{H1, H2, H3\}$: Redefines band widths based on distributional thresholds, though these would ultimately be fixed values. Specifically:

$$P_{H_1}^{high} = \bar{v}_H, \quad P_{H_2}^{\bar{v}} + \sigma_H, \quad P_{H_3}^{low} = P_{H_2}^{high} + 0.01$$

Multipliers are adjusted incrementally across these new bands, with lower segments receiving slightly reduced rates and higher segments receiving increased rates, as shown in [Table 3.11.](#)

[Table 3.11: Counterfactual 3.4's New Band Price Ranges, Counts, and Multipliers](#)

Band	Band Range Low	Band Range Cap	Dwelling Count	Multiplier
A1	£0.00	£142,553.63	2,621,649	0.500
A2	£142,553.64	£186,758.73	2,621,649	0.667
B1	£186,758.74	£221,782.84	2,211,989	0.768
B2	£221,782.85	£256,806.94	2,174,621	0.788
C1	£256,806.95	£305,603.61	2,700,242	0.879
C2	£305,603.62	£354,400.27	2,305,069	0.899
D1	£354,400.28	£409,896.96	2,091,770	0.990
D2	£409,896.97	£465,393.64	1,513,362	1.010
E1	£465,393.65	£545,127.21	1,425,088	1.212
E2	£545,127.22	£624,860.77	850,957	1.232
F1	£624,860.78	£700,626.64	514,327	1.434
F2	£700,626.65	£776,392.50	333,918	1.454
G1	£776,392.51	£1,233,726.67	691,582	1.657
G2	£1,233,726.68	£1,691,060.83	146,112	1.677
H1	£1,691,060.84	£2,532,137.76	70,109	2.000
H2	£2,532,137.77	£3,724,885.43	20,722	2.500
H3	£3,724,885.44	∞	10,435	3.000

Category 4: Hybrid Band-Value

Category 4 combines band restructuring with value-based multipliers to more closely align tax liabilities with underlying property values. This category contains only one counterfactual, and it is a hybrid of two other approaches: the 17-band structure explored in the Counterfactual 3.4 and the approach to reweighting the multipliers based on the mean value of the band redistributed explored in Counterfactual 2.4.

As in 3.4, the 17-band structure eliminates Band D, thus there is no anchor band with a 1.000 multiplier. To preserve continuity with the role of Band D as the reference point, a new anchor is defined as the mean property value across all dwellings in the combined D1 and D2 bands. This implies that D1 will receive a multiplier below 1.000 and D2 will be above 1.000. Formally, the mean property value for each new band is:

$$\bar{v}_b^{new} = \frac{\sum_{i \in b} v_i}{n_b}$$

, where v_i = estimated, contemporary value for dwelling i

and n_b = number of dwellings in band b

The anchor mean is defined as the average of contemporary values across all dwellings in D1 and D2:

$$\bar{v}_D^{anchor} = \frac{(\bar{v}_b^{new} n_{D_1} + \bar{v}_b^{new} n_{D_2})}{n_{D_1} + n_{D_2}}$$

The multipliers for each new band as then expressed relative to the anchor value:

$$m_b = \frac{\bar{v}_b^{new}}{\bar{v}_D^{anchor}}$$

This hybrid design simultaneously addresses regional inequity through a national reassessment process; wide-band distortions by implementing finer bands; and proportional erosion by anchoring to mean values rather than historical ratios. The resulting multipliers are shown in Table 3.12.

Table 3.12: Counterfactual 4.1's New Band Price Ranges, Counts, and Multipliers

Band	Band Range Low	Band Range Cap	Dwelling Count	Estimated Avg Value	Proposed Multiplier
A1	£0.00	£142,553.63	2,621,649	£113,208.69	0.280
A2	£142,553.64	£186,758.73	2,621,649	£165,028.78	0.409
B1	£186,758.74	£221,782.84	2,211,989	£204,309.14	0.506
B2	£221,782.85	£256,806.94	2,174,621	£239,170.25	0.592
C1	£256,806.95	£305,603.61	2,700,242	£280,545.24	0.694
C2	£305,603.62	£354,400.27	2,305,069	£329,221.29	0.815
D1	£354,400.28	£409,896.96	2,091,770	£380,806.74	0.943
D2	£409,896.97	£465,393.64	1,513,362	£436,020.17	1.079
E1	£465,393.65	£545,127.21	1,425,088	£501,522.98	1.241
E2	£545,127.22	£624,860.77	850,957	£582,174.27	1.441
F1	£624,860.78	£700,626.64	514,327	£659,676.24	1.633
F2	£700,626.65	£776,392.50	333,918	£735,643.74	1.821
G1	£776,392.51	£1,233,726.67	691,582	£935,864.96	2.317
G2	£1,233,726.68	£1,691,060.83	146,112	£1,421,304.23	3.518
H1	£1,691,060.84	£2,532,137.76	70,109	£2,003,574.56	4.960
H2	£2,532,137.77	£3,724,885.43	20,722	£2,957,677.57	7.321
H3	£3,724,885.44	∞	10,435	£4,489,368.92	11.113

Category 5: Value-based Tax Systems

Category 5 encompasses counterfactuals that replace the banded Council Tax structure with value-based systems, in which household liabilities are calculated directly as a proportion of assessed property value. This category replaces the banded system entirely with value-based taxation, allowing liabilities to vary continuously with property value.

This category includes four counterfactuals, grouped into two broad subcategories. The first adopts a proportional ad valorem structure similar to property tax systems used in many other countries. The second introduces a progressive continuous rate schedule, in which tax rates increase with property value, capped at an

annual rate of 1 percent for the highest-value dwellings. In short, these scenarios test two distinct models; one that emphasises proportionality and another that emphasises progressivity.

Ad valorem tax structures are common across OECD countries and offer several technical advantages over banded systems. They allow for more precise rate-setting, ensure proportional increases in liabilities with respect to property value (and potentially other factors such as income or deprivation), and eliminate the inequities caused by broad value bands with flat liabilities. They can also accommodate means-tested relief mechanisms such as Council Tax Support (CTS). However, moving to an individualised assessment model presents significant challenges. It requires more robust valuation systems, higher administrative capacity, and careful policy design to minimise volatility. Even small valuation errors or delays can create disproportionate impacts on household liabilities. Effective implementation would depend on reliable, regularly updated automated valuation models (AVMs), potentially supplemented by private-sector data sources. International examples such as Denmark and Canada demonstrate the importance of regular revaluations and modern digital appraisal infrastructure in sustaining public trust in value-based property taxation (OECD, 2025).

Given the scope of reform in this category, each counterfactual also considers the role of Council Tax Support. Some scenarios retain CTS to protect vulnerable households, while others remove it to isolate the underlying distributional effects of a pure value-based tax. Because bands are eliminated entirely, the evaluation of these counterfactuals differs from earlier categories. Rather than focusing on band placement, the analysis examines the average and distribution of liability changes across all dwellings, as nearly all households experience some degree of change. This provides a clearer picture of how proportional and progressive value-based systems reshape the distribution of tax burdens.

Flat Ad Valorem Mill Levy (5.1)

Counterfactual 5.1 replaces the banding system with a flat value-based rate, in which liabilities are set as a fixed percentage of the contemporary estimated value. This approach mirrors ad valorem property tax systems used in

many other jurisdictions, including municipalities across the United States and Canada, and provides a benchmark for a fully proportional system in which each dwelling faces the same effective tax rate.

The mill levy r^0 is set to generate the current pre-CTS total revenue, ensuring revenue neutrality:

$$r^0 = \frac{\sum_{i=1}^N l_i^{orig}}{\sum_{i=1}^N v_i}$$

, where l_i^{orig} = current liability for dwelling i

and N = total number of dwellings

and v_i = estimated, contemporary value for dwelling i

Therefore, a dwelling's pre-CTS liability, l_i^{new} , is formally:

$$l_i^{new} = r^0 \times v_i$$

After the pre-CTS rate is derived, CTS is still modeled as a relief mechanism at the current average percentage for the property's former band within its local authority district. This maintains the existing support distribution for analytical purposes, although such an approach may not be feasible in practice without bands. In a flat tax system, CTS would likely be redesigned around income, deprivation, or other direct measures of need.

Flat Ad Valorem Mill Levy with Deprivation-based CTS (5.2)

Counterfactual 5.2 builds on 5.1 by retaining the flat ad valorem tax structure while redistributing relief using area-level income deprivation as a proxy for household need. Instead of preserving support based on historical band averages, relief is reallocated across dwellings according to the income deprivation score of each Lower Super Output Area (LSOA), with higher levels of deprivation corresponding to larger proportional rebates.

Taking the pre-CTS flat tax rate from 5.1, r^0 , each dwelling i in LSOA j receives a discount factor f_j based on the income deprivation scores. As the income deprivation is an aggregate representing the percentage of the LSOA population that is considered income deprived, $d_j \in (0,1)$ with real values ranging between 0.003 and 0.609. The discount factors are scaled to aggregate rebates equal to the current CTS total in England, C . Formally, the discount factor per LSOA is:

$$f_j = \frac{d_j^\alpha}{\sum_k d_k^\alpha n_k} \times C$$

, where n_k = number of dwellings in LSOA k

The parameter α governs the magnitude of the income deprivation's influence on the discount. If $\alpha = 1$, relief is directly proportional to the income deprivation score. If $\alpha < 1$ relief is distributed more evenly, and if $\alpha > 1$ then weighting is more concentrated to highly deprived areas. Thus, in this simulation $\alpha = 1.5$ to amplifying relief to the most income deprived LSOAs.

The new liability for each dwelling i is expressed:

$$l_i^{new} = r^0 v_i - f_j r^0 v_i$$

, where v_i = dwelling i 's estimated contemporary price

By design, this approach maintains overall post-support revenue close to the current system while redistributing relief toward more deprived areas. However, the use of LSOA-level deprivation introduces limitations, as it serves only as a proxy for household-level ability to pay. Deprived households may reside in relatively affluent areas, and vice versa, while the underlying data are updated infrequently. More granular or real-time measures of income would provide a more precise basis for targeting support in practice.

Progressive Value-Based Tax (1% Cap) (5.3)

Counterfactual 5.3 substitutes the existing system with a continuous progressive property tax schedule, in which the effective tax rate increases smoothly with property value, capped at a maximum of 1.0 percent. Unlike the flat structure in 5.1, this design introduces progressivity directly into the rate schedule while maintaining a value-based framework.

For dwelling i with assessed value v_i , the provisional rate is:

$$r_i = \min \left(\frac{v_i - v_{min}}{v_{\cap} - v_{min}} r_{max}, r_{max} \right)$$

, where v_{min} = the min comtemporany price across all dwellings

and $v_{\cap} = \bar{v}_H + \sigma_H$

and $r_{max} = 0.01 = \text{rate cap}$

The liability for dwelling i is therefore:

$$l_i = r_i v_i$$

The schedule is calibrated such that, under national revenue neutrality, most properties remain below the 1.0 percent cap, with only the highest-value dwellings approaching the upper bound. Lower-value dwellings face below-average rates, while higher-value dwellings are taxed at progressively increasing rates, with mid-range properties near the point where the schedule intersects the flat rate from 5.1.

To limit sensitivity to extreme outliers, the cap is anchored at one standard deviation above the mean value of Band H (clipped to the observed price range), ensuring that the highest rates apply to the upper end of the distribution without being driven by a small number of ultra-high-value observations. This specification implies that very low-value dwellings may face minimal liabilities, while capped high-value dwellings may be taxed

below their proportional share. Alternative functional forms could smooth the schedule at either end, but the linear specification provides a transparent benchmark.

For comparability, Council Tax Support (CTS) is applied retrospectively using the same approach as in 5.1, although such a system would likely require a redesigned support mechanism in practice.⁴⁸

Progressive Value-Based Tax (1.0% Cap) with Deprivation-based CTS (5.4)

Counterfactual 5.4 combines the progressive continuous rate from 5.3 with the deprivation-based adjustment from 5.2. Tax liabilities rise smoothly with property value, capped at 1.0 percent, and are then reduced proportionally according to the income deprivation score of the property's LSOA. The system is again revenue neutral before the deprivation adjustment, which redistributes part of the liability to favor more deprived areas. LSOA income deprivation is again used to redistribute the current national CTS with a $\alpha = 1.5$ to assign increased relief to the more deprived areas.

The combined effect is that tax liabilities reflect both property wealth and area deprivation. Low-value dwellings in deprived areas benefit most, paying substantially less than under the current banded system. High-value dwellings in affluent areas face the highest effective rates, often close to the 1.0 percent cap. High-value dwellings in deprived areas pay more than low-value ones but still receive partial relief, softening their burden.

This design considers that ability to pay is influenced by both property wealth and socioeconomic factors. Although LSOA-level deprivation is only an approximate measure and could potentially be substituted with more detailed income-linked indicators, the approach offers a practical, area-based method using currently available

⁴⁸ Instead of a straight linear increase, the progression of effective tax rates could be shaped using other functions. An exponential or logistic curve would raise rates slowly at the bottom and more sharply in the middle of the distribution, then flatten at the top before the cap, reducing pressure on the very highest-valued properties. A power function could instead concentrate the increase toward the upper end, protecting lower-value households from sudden jumps. Alternatively, a spline-based schedule anchored at selected value percentiles could be designed to hit policy-chosen benchmarks. These options illustrate that while the linear form is the simplest, policymakers can flexibly adjust the rate schedule to balance equity, stability, and policy objectives.

data. This framework demonstrates how value-based taxation may be integrated with deprivation-sensitive relief measures to create a system that is more equitable in terms of both vertical and horizontal fairness compared to current models.

Table 3.13: Summary of All Simulation Configurations, including Bands, Multipliers, and Dwelling Counts

Category	Name	ID	Bands	Dwellings per Band	Multipliers	Purpose
Revaluation Only	Revaluation Baseline	1.1	Current: {A, B, C, D, E, F, G, H}	Current (Nationally): {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Current: {0.667, 0.778, 0.889, 1.000, 1.222, 1.444, 1.667, 2.000}	Establishes the equity gains from updating valuations alone without structural reform.
Rewighted Multipliers	Adjusted Upper-Band Multipliers (Scotland)	2.1	Current: {A, B, C, D, E, F, G, H}	Current (Nationally): {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.310, 1.630, 1.960, 2.450}	Tests modest progressivity by increasing tax burdens on higher-value properties.
	Enhanced Upper-Band Multipliers (Scotland Purposed)	2.2	Current: {A, B, C, D, E, F, G, H}	Current (Nationally): {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.410, 1.830, 2.300, 3.000}	Evaluates a more aggressive increase in progressivity concentrated at the top.
	Band Midpoint Value Multipliers	2.3	Current: {A, B, C, D, E, F, G, H}	Current (Nationally): {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.310, 1.630, 1.960, 2.450}	Aligns tax rates to underlying values using band midpoints.
	Mean Value-Based Multipliers	2.4	Current: {A, B, C, D, E, F, G, H}	Current (Nationally): {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.410, 1.830, 2.300, 3.000}	Uses observed mean values to better reflect the true distribution.
Band Structure Reform	Add Top Band (Wales)	3.1	Fixed: {A, B, C, D, E, F, G, H, I}	Derived: {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 72.3K, 29.0K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.222, 1.444, 1.667, 2.000, 2.333}	Adds a new band to better capture high-value properties.
	Split Upper Bands	3.2	Fixed: {A, B, C, D, E, F, G1, G2, H1, H2}	Derived: {5.2M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 72.3K, 29.0K}	Fixed: {0.667, 0.778, 0.889, 1.000, 1.222, 1.444, 1.667, 2.000, 2.333, 2.667}	Reduces distortion at the top by narrowing band widths.
	Split Lower Band	3.3	Fixed: {A1, A2, B, C, D, E, F, G, H}	Derived: {2.6M, 2.6M, 4.4M, 5.0M, 3.6M, 2.3M, 848.2K, 837.7K, 101.3K}	Fixed: {0.556, 0.667, 0.778, 0.889, 1.000, 1.222, 1.444, 1.667, 2.000}	Targets relief toward lower-value properties.
	Full Band Splitting	3.4	Fixed: {A1, A2, A3, B1, B2, C1, C2, D1, D2, E1, E2, F1, F2, G1, G2, H1, H2, H3}	Derived: {2.6M, 2.6M, 2.2M, 2.1M, 2.7M, 2.3M, 2.1M, 1.5M, 1.4M, 851.0K, 514.3K, 333.9K, 691.6K, 146.1K, 70.1K, 20.7K, 10.4K}	Fixed: {0.500, 0.667, 0.768, 0.788, 0.879, 0.899, 0.990, 1.010, 1.212, 1.232, 1.434, 1.454, 1.657, 1.677, 2.000, 2.500, 3.000}	Minimizes within-band inequities across the distribution.
Hybrid Band-Value	Split Bands with Mean Value Multipliers	4.1	Fixed: {A1, A2, A3, B1, B2, C1, C2, D1, D2, E1, E2, F1, F2, G1, G2, H1, H2, H3}	Derived: {2.6M, 2.6M, 2.2M, 2.1M, 2.7M, 2.3M, 2.1M, 1.5M, 1.4M, 851.0K, 514.3K, 333.9K, 691.6K, 146.1K, 70.1K, 20.7K, 10.4K}	Fixed: {0.280, 0.409, 0.506, 0.592, 0.694, 0.815, 0.943, 1.079, 1.241, 1.441, 1.633, 1.821, 2.317, 3.518, 4.960, 7.321, 11.113}	Combines banding with value-based rates to approximate proportional taxation.
Value-Based Tax Systems	Flat Ad Valorem Mill Levy	5.1	Bandless	Bandless	Not Applicable	Implements a proportional tax directly tied to property value.
	Flat Ad Valorem Mill Levy with Deprivation-based CTS	5.2	Bandless	Bandless	Not Applicable	Combines proportional taxation with targeted relief based on deprivation.
	Progressive Value-Based Tax	5.3	Bandless	Bandless	Not Applicable	Introduces a progressive rate structure increasing with property value.
	Progressive Value-Based Tax with Deprivation-based CTS	5.4	Bandless	Bandless	Not Applicable	Combines progressive taxation with targeted deprivation-based relief.

5 Results

To assess the effectiveness of each reform, outcomes are compared across all modeled counterfactual scenarios, using both the existing system and a simple revaluation benchmark as reference points. Because each counterfactual builds upon a common statistical revaluation, differences in outcomes reflect the impact of structural reforms rather than changes in valuation methodology. Here, we evaluate five principle dimensions; they are the redistribution of tax liabilities, the proportionality of taxes relative to property value, the progressivity of effective tax rates across the value distribution, the alignment of tax burdens with ability-to-pay factors such as income and deprivation, and spatial consistency in effective tax rates across local authorities.

Across these dimensions, three consistent findings emerge. First, the majority of improvements in tax equity arise from revaluation alone. Updating property values to contemporary market conditions corrects a large share of the misalignment between tax liabilities and property values that has accumulated since the early 1990s. Second, the magnitude of equity gains is driven more by the scale of structural reform than by the category of reform. Incremental adjustments—such as modest multiplier changes or limited band splitting—produce relatively small improvements, while more comprehensive reforms, including hybrid band-value systems and value-based taxation, generate substantially larger gains in proportionality and distributional equity. Third, all reforms involve a trade-off between equity gains and disruption. Policies that most closely align tax liabilities with property values tend to deliver the largest improvements in equity, but also produce greater variation in household tax liabilities, particularly for high-value properties.

5.1 Outcomes of a Simple Revaluation

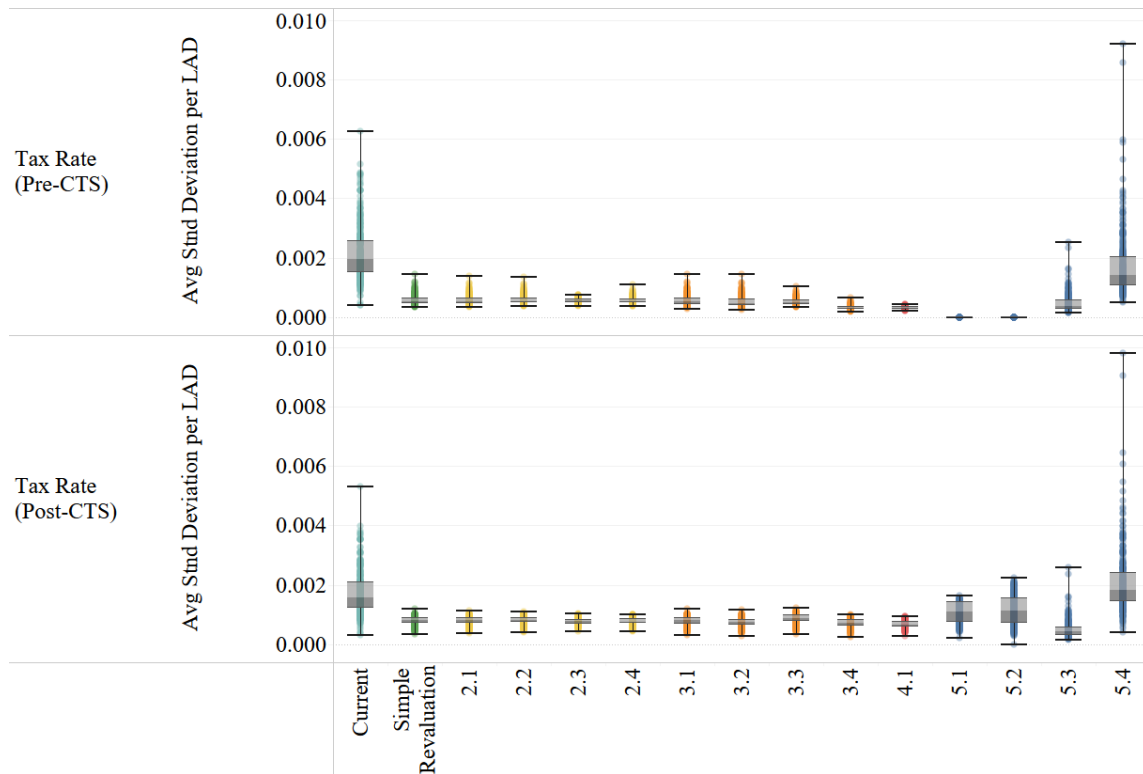
Revaluation is the primary driver of equity improvements across all counterfactuals. The results from Counterfactual 1.1 show that outdated valuations and uneven inflation have led to widespread mis-banding, which underpins much of the distortion in the current system.

Under the existing framework, many properties are assigned to inappropriate bands based on 1991 valuations, resulting in significant horizontal inequities. Following revaluation, approximately 51% of dwellings shift bands, reflecting the scale of misalignment, as shown in Table 3.17 in Appendix B. This produces both “winners” (27%) and “losers” (24%), though the distribution of these changes is far from uniform.

The adjustment has a strong regional dimension. High-growth areas in the South that were previously under-taxed see widespread upward band shifts, whereas many properties in the North and Midlands fall into lower bands after revaluation. This means the tax burden is realigned toward regions that experienced the greatest property appreciation, correcting the implicit subsidy that high-value southern homes enjoyed under the current system.

Revaluation also substantially improves consistency in effective tax rates. As shown in Figure 3.3, the dispersion of effective tax rates—measured as the average standard deviation across and within bands—is significantly narrower under revaluation than under the status quo. This indicates that a large share of existing disparities arises from misallocated properties rather than from the structure of the tax schedule itself.

Figure 3.3: Spread of Average Standard Deviation of Tax Rate per LAD for All Counterfactuals

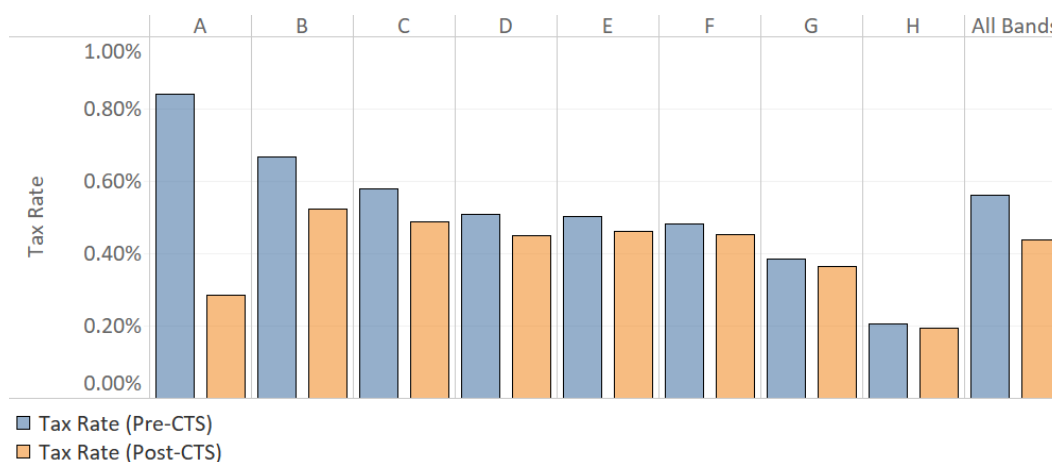


Note: Box-and-whisker plots compare the dispersion (measured by the avg standard deviation) of tax rates across LADs for each counterfactual, split by pre- and post-CTS. Narrower boxes indicate greater proportionality within bands.

5.2 Distributional Patterns: Winners and Losers

Although the simple revaluation corrects much of the inflation-driven misallocation by assigning dwellings to more appropriate bands (and implicitly updating the distribution of Council Tax Support), it does not establish a more proportional tax framework within local authorities. The existing band multipliers are retained, meaning that regressive differences in effective tax rates across bands persist. [See Figure 3.4.] This distinction is important, as it illustrates that revaluation substantially improves horizontal equity, but leaves vertical equity largely unchanged.

Figure 3.4: Pre- and Post-CTS Estimated Tax Rate by Band



Bars show the average effective tax rate per band before (blue) and after (orange) CTS. This illustrates how CTS alters the relationship between liability and property value.

The subsequent counterfactuals build on this benchmark by introducing structural changes to the tax schedule. To summarise their effects, the distribution of winners and losers provides a useful and comparable measure across all scenarios. Because not all counterfactuals retain the same banding structure – or any banding at all – changes in tax liability offer a more consistent basis for comparison than changes in band assignment.

Across these scenarios, several consistent patterns emerge.

First, in nearly all revenue-neutral reforms, winners outnumber losers. This reflects the concentration of dwellings in lower and middle value bands, where relatively small increases on higher-value properties can finance widespread, though often modest, reductions for a large share of households. Second, the balance between the number of winners and the magnitude of changes depends on how broadly tax increases are applied across the distribution. Reforms that concentrate increases at the very top tend to produce many winners with relatively small gains, while reforms that spread increases more broadly generate fewer winners but larger average changes. This can be seen in Table 3.18 in Appendix B.

Incremental reforms focused on the upper end of the distribution – such as matching Scotland’s multipliers (2.1), matching Scotland’s proposed multipliers (2.2), adding a top band (3.1), and splitting the highest bands

(3.2) – illustrate the first pattern. In these cases, more than 80% of dwellings benefit from lower liabilities. However, the average gains are relatively modest, reflecting the limited scale of redistribution. For example, 2.1 and 2.2 produce average annual savings of approximately £38 and £81, respectively, financed by increases of roughly £165 to £342 among higher-value properties. Similar outcomes are observed in 3.1 and 3.2, where changes are concentrated at the top of the distribution and diffused across a large number of lower-value dwellings.

More comprehensive multiplier reforms – such as band range midpoint weighting (2.3) and estimated mean value weighting (2.4) – extend adjustments across all bands. These reduce the share of winners to roughly two-thirds of dwellings but increase the magnitude of changes. Average savings for beneficiaries rise to approximately £220 and £112 in 2.3 and 2.4, respectively, while losses are more broadly distributed, with average increases of £559 and £326. This reflects a shift from narrowly targeted redistribution toward system-wide rebalancing, where gains and losses are more evenly shared across the distribution.

Reforms that explicitly target relief at the lower end of the distribution – such as splitting the lowest band (3.3) and splitting all bands (3.4) – produce a different pattern. Because a large share of dwellings is concentrated in the lowest bands, even small increases elsewhere result in a high proportion of dwellings being classified as “losers.” In these cases, fewer than 15% of households benefit, while nearly 88% experience increases. However, the vast majority of these losses are small in magnitude; over 90% of affected dwellings face increases of less than £100 per year. This highlights how policies targeting relief at the bottom of the distribution can shift many households from neutral to “loser” status without materially worsening outcomes.

More structurally balanced reforms – such as the hybrid band and value-based system (4.1) – produce a more even distribution of winners and losers. In this case, approximately 55% of dwellings benefit while 45% face increases, with average changes of around –£238 for winners and +£329 for losers. This reflects the combined

effect of finer banding and value-based multipliers, which spread adjustments more evenly while still improving overall proportionality.

Finally, value-based systems in Category 5 generate the most pronounced redistributive patterns. Flat mill levy systems (5.1 and 5.2) produce a majority of winners (approximately 62.5% and 57% respectively), while progressive schedules concentrate increases on a small number of high-value properties. In the most extreme case (5.3), nearly all dwellings (98.4%) benefit, with increases concentrated among a very small group facing average increases exceeding £1,700 annually. The deprivation-adjusted variant (5.4) moderates this effect, producing approximately 79% winners, but retains the same underlying structure. These models illustrate the upper bound of redistribution achievable under revenue neutrality.

In all scenarios, the allocation of gains and losses demonstrates a typical trade-off. Policies that target increases toward a limited group of high-value properties can lead to modest benefits for most stakeholders. Conversely, broader reforms distribute outcomes more uniformly, resulting in greater changes but fewer recipients of positive outcomes. The balance between the scope and magnitude of redistribution is a key consideration when evaluating results across all counterfactuals.

5.3 Tax Proportionality and Vertical Equity

A central objective of the reforms is to improve vertical equity by aligning tax liabilities more closely with property values. Under the current Council Tax, tax paid has only a weak relationship with a home's market value. The effective tax rates decline as the bands increase (apart from Band A when accounting for Council Tax Support). Empirically, the Pearson correlation coefficient between estimated dwelling values and average Council Tax across all properties is 0.52, with only slight increases when factoring in CTS. [See Figure 3.5.]

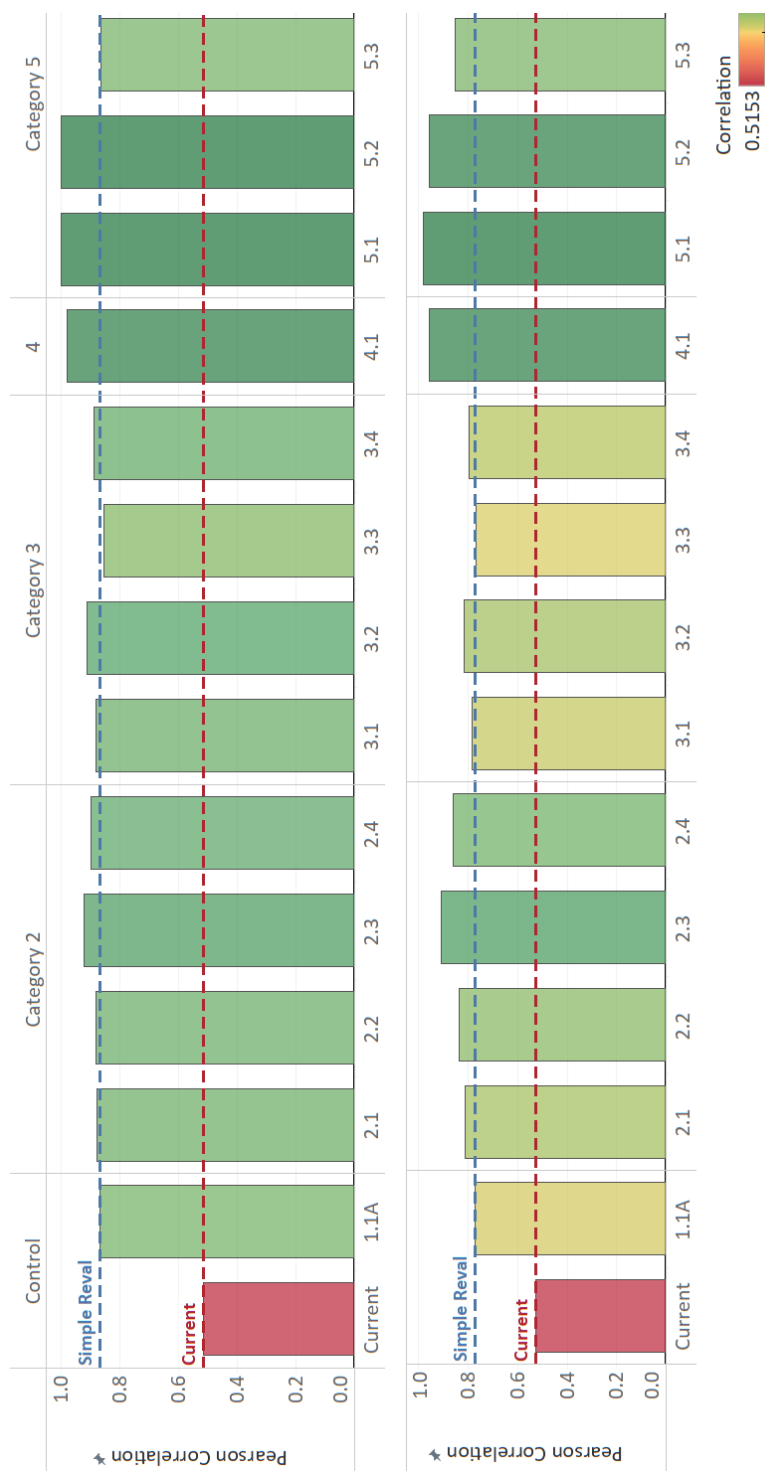
All counterfactuals improve upon this baseline, though to varying degrees. The simple revaluation produces a substantial increase, raising the correlation to approximately 0.87 prior to CTS. Among banded systems,

Counterfactual 4.1 performs especially well, reaching nearly 0.98, demonstrating how finer banding combined with value-weighted multipliers can closely approximate proportional taxation. By construction, flat ad valorem systems (5.1 and 5.2) achieve a near-perfect alignment between tax liabilities and property values, establishing an upper bound for proportionality within this framework.

By contrast, the continuously progressive schedules in 5.3 and 5.4 do not materially increase the correlation beyond the revaluation benchmark. This reflects the non-linear structure of these systems, in which higher-value properties face increasing marginal rates up to the cap, rather than a strictly proportional relationship. Across all counterfactuals, the application of Council Tax Support reduces the observed correlation between tax liabilities and property values, as relief is not proportionally to property values but is targeted non-linearly toward households with greater need. This is mostly driven by the need-based CTR components of CTS. In practice, this reduces tax burdens at the lower end of the distribution (primarily in Band A) and further flattens the effective tax–value gradient. Moreover, gaps in CTR coverage and imperfect targeting (where some eligible households do not receive full or timely relief) introduce additional noise, further weakening the observed correlation. Thus, Figure 3.5 shows that the correlation is lower post-CTS for all counterfactuals, including moving the flat ad valorem tax counterfactuals to a now imperfect 0.98 and 0.96 for 5.1 and 5.2 respectively.

Importantly, improvements in proportionality extend beyond property values alone. Because property values are correlated with income and wealth, strengthening the link between tax liabilities and property values also improves alignment with households' underlying economic capacity. This effect is most pronounced in counterfactuals such as 4.1 and 5.1, which substantially reduce regressivity while implicitly linking liabilities to ability to pay.

Figure 3.5: Pearson Correlations between Liabilities and the Estimated Price by Control and Counterfactual



Note: Bars display how correlation strength changes between benchmark and counterfactual scenarios, separated by pre- and post-CTS.

5.4 Regional Consistency and Horizontal Equity Across Local Authorities

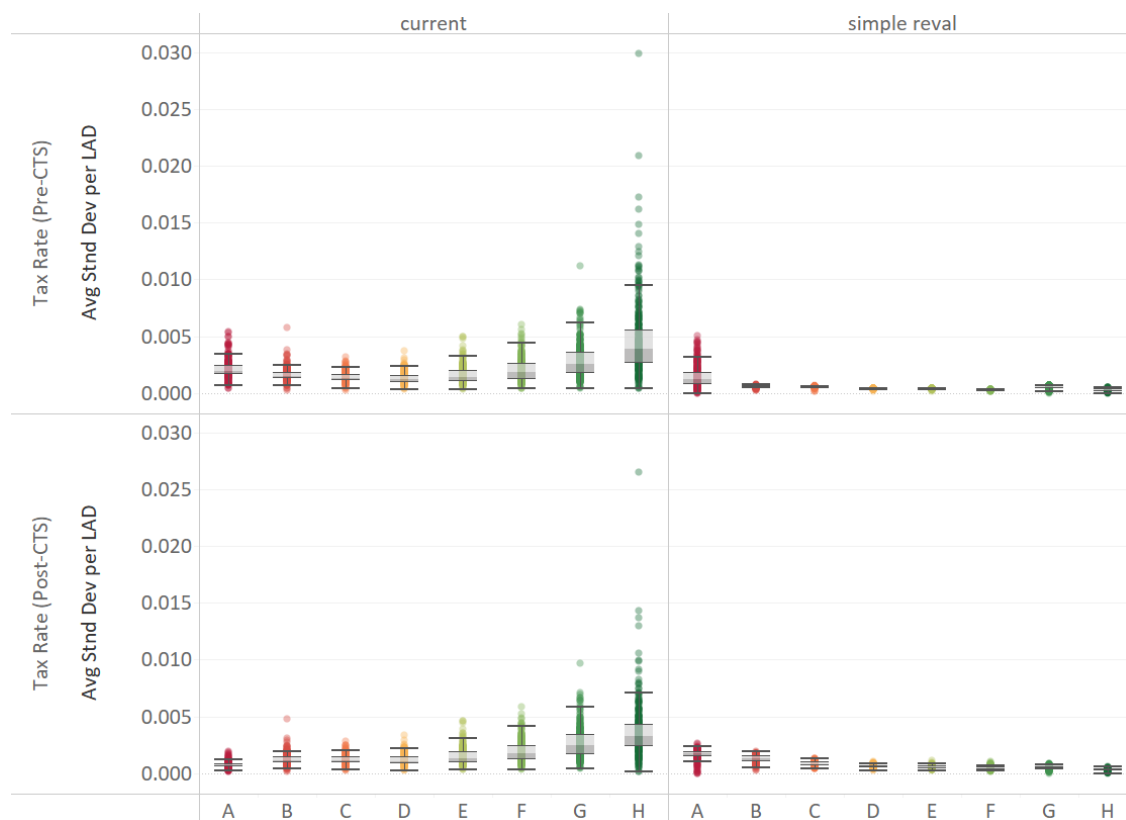
Regional consistency refers to the degree to which taxpayers in different areas face similar effective tax rates on properties of equivalent value. To measure consistency in like-valued dwellings across local authorities in England, we examined the spread of average effective tax rates (tax as a percentage of property value) across local authorities under each counterfactual. Under the current system, the dispersion is extremely wide, with some LADs averaging effective rates close to or above 0.8 percent of property value while others are around 0.2 percent. Such divergence reflects a profound lack of horizontal equity between regions.

The simple revaluation (1.1A) considerably narrows this spread by updating the tax base and starting from a nationally normalised rate structure. For properties of similar value, those located in higher-value areas such as London see their effective rates rise, while dwellings in more deprived local authorities experience relative rate reductions converging toward the national median. Revaluation therefore removes much of the valuation-driven component of regional disparity.⁴⁹

Figure 3.3 depicts the distribution of the average standard deviations in the tax rate across properties in each of the 309 local authorities for each counterfactual. Under the current system, the spread is extremely large, reflecting both mis-banding and divergent local tax settings. Revaluation alone sharply compresses this variation, which is summarised in Figure 3.6 below. Other counterfactuals achieve incremental improvements beyond 1.1A, but the largest gains are observed under flat ad valorem systems (5.1 and 5.2), which produce near-perfect alignment across local authorities prior to CTS application.

⁴⁹ Note that these results reflect an initial normalization of local rates, abstracting from existing differences in council budget requirements. In practice, equalizing rates would require separate fiscal adjustments to address distributional funding effects.

Figure 3.6: Spread of Avg Standard Deviation of Tax Rate Per LAD and Band for the Current and Simple Revaluation Benchmarks



Box-and-whisker plots compare the dispersion of tax rates across LADs for each band, split by pre- and post-CTS. Narrower boxes indicate greater proportionality within bands.

The application of Council Tax Support reintroduces variation. Because CTR is concentrated in lower bands and varies across local authorities, it leads to uneven reductions in effective tax rates. This effect is particularly evident in counterfactuals involving extensive band restructuring (3.4 and 4.1), where interactions between band adjustments and local property distributions result in somewhat wider spreads once CTS is applied.

5.5 Tax Rate Structures and Progressivity

Each reform implies a distinct relationship between property value and the effective tax rate. Figure 3.18 illustrates this functional relationship under the status quo and selected counterfactuals by plotting third-degree polynomial trend lines against property value.⁵⁰

Under the current system, the fitted curve is strongly concave, indicating pronounced regressivity: lower-value properties face higher effective rates, while rates decline as property values increase. Once a property exceeds the top band threshold, liabilities no longer rise proportionally, producing a sharp downward slope. The simple revaluation (1.1A) improves band assignment but leaves this structure largely unchanged.

Incremental reforms produce only modest adjustments. The curve remains downward sloping, though slightly flatter at the top as rates increase for higher-value properties. More substantive reforms, by contract, largely change and sometime eliminate this regressive slope. By tightening bands and aligning multipliers with underlying values, these scenarios produce a near-linear relationship across most of the distribution, approximating proportional taxation. More aggressive reforms, such as 2.3, introduce a clear upward slope, concentrating liabilities further at the top.

Category 5 counterfactuals represent the most pronounced shift. Flat ad valorem systems (5.1 and 5.2) produce a horizontal line, reflecting pure proportionality. In contrast, continuous progressive systems (5.3 and 5.4) generate an upward-sloping curve, with rates increasing alongside property values before flattening at the cap. These designs represent the most progressive structures among the scenarios considered.

⁵⁰ To visualize the tax–value relationship across roughly 23 million dwellings, property values were partitioned into 100 equal-width bins. Mean effective tax rates and values were calculated per bin, and a low-order polynomial (degree 3) was fit to these binned points to approximate the functional form of the schedule. This smoothing captures the overall structure while down-weighting extreme tail effects, which may be understated due to binning.

5.6 Spatial Equity and Redistribution Patterns

Synthesizing the results across all counterfactuals highlights the central role of spatial disparities in the current system. Under the existing framework, effective tax rates vary widely across local authorities, with many high-value areas, particularly in London and the Southeast, facing lower effective rates than less affluent regions. Map 3 illustrates this misalignment, showing that high-price areas are often taxed at relatively low rates, while lower-price areas face higher effective burdens. The simple revaluation (1.1A) corrects much of this imbalance by aligning properties with contemporary values, raising effective rates in high-value regions and lowering them elsewhere. As a result, the geographic pattern of winners and losers is consistent across reforms, with the North and Midlands generally benefiting and London and the Southeast facing higher liabilities. These changes reflect the correction of long-standing valuation distortions rather than the introduction of new inequities.

Beyond revaluation, the structure of the tax system determines how far these spatial adjustments extend. Expanding bands (Category 3 and 4) reduces within-band disparities, but meaningful improvements require multipliers that reflect underlying property values. Scenarios such as 2.4 and 4.1 demonstrate that combining finer banding with value-based rates produces substantial gains in both proportionality and spatial equity. Value-based systems in Category 5 extend this further by directly linking liabilities to property values, producing the largest reductions in regional disparities. Across all scenarios, the most significant improvements in spatial equity arise when revaluation is paired with structural reforms that redistribute liabilities across the national property value distribution.

6 Conclusion

The results imply that all reform scenarios outperform the current Council Tax system in terms of equity and proportionality. Any move away from the 1991-based valuation framework, whether through simple revaluation or more extensive structural reform, would therefore represent a material improvement. Among these, revaluation emerges as the most important mechanism. Updating property assessments to contemporary market

values corrects the majority of horizontal and vertical inequities that have accumulated over time, largely driven by uneven regional price growth. Even a simple reassignment of properties into existing bands produces substantial improvements in the alignment between tax liabilities and property values.

At the same time, these gains underscore that revaluation is inherently disruptive. Because property values have evolved unevenly across regions, updating the tax base results in widespread reassignment of dwellings and significant shifts in tax liabilities. In effect, even a “minimal” reform constitutes a substantial redistribution. This implies that meaningful reform is already unavoidable if equity is to be restored. It also reframes the policy question; once revaluation occurs, the distinction between marginal and more comprehensive reforms becomes less pronounced, as both operate on an already transformed distribution. Revaluation therefore presents both a challenge and an opportunity; while politically difficult due to its widespread impact, it also creates a natural point at which broader structural changes can be implemented.

However, revaluation alone does not resolve the structural limitations of the banded system. Even with updated values, the schedule remains intrinsically regressive, with higher-value properties facing lower effective tax rates relative to their value. Incremental reforms, such as modest multiplier adjustments or additional bands, can reduce these distortions and improve proportionality with relatively limited additional disruption. Band splitting smooths the tax schedule and reduces within-band inequities, but does not fully eliminate the underlying regressivity.

Given this, the results highlight a fundamental trade-off between proportionality and social stability. Counterfactual 4.1 demonstrates that the banded system can be substantially modernised by combining finer banding with value-aligned multipliers. This approach delivers large gains in proportionality and spatial equity while preserving a key advantage of banding – insulation from valuation error. Because tax liabilities depend on band assignment rather than precise point estimates, moderate inaccuracies in automated valuation models do not

translate directly into financial outcomes, provided properties are placed in the correct band. In this sense, banding smooths underlying valuation uncertainty.

By contrast, value-based systems such as Counterfactual 5.2 eliminate distortions from banding entirely, linking liabilities continuously to estimated property values. When combined with a redesigned support mechanism, this produces some of the largest improvements in both vertical and spatial equity, aligning tax burdens more closely with underlying property wealth. Such systems are also widely used internationally, forming the basis of property taxation in many OECD countries, and are often regarded as a benchmark for proportional taxation. However, this gain in precision introduces new challenges. Without banding, valuation error passes directly into tax liabilities, and the absence of an implicit upper bound within bands means that high-value properties can face very large increases in absolute terms. Policy tools such as caps, deferrals, or circuit-breakers can be introduced to mitigate these effects, though doing so reintroduces elements of distortion into the system. Even with such constraints, value-based systems tend to concentrate a disproportionate share of adjustment on a small segment of the distribution. As a result, while these systems achieve near-perfect proportionality in theory, they do so at the cost of greater sensitivity to valuation accuracy, higher volatility at the top end, and increased potential for political resistance.

Collectively, these findings indicate that selecting between banded and value-based systems involves considerations beyond mere accuracy, encompassing aspects of institutional design amid uncertainty. Banded systems trade some proportional precision for increased robustness and stability, whereas value-based systems enhance proportionality but rely on more stringent assumptions regarding valuation accuracy and political feasibility. Given the significant redistribution triggered by revaluation, the pertinent policy issue concerns how to structure this disruption, rather than whether it should take place.

A related implication concerns the institutional structure of the tax system. Because the largest distortions arise from regional differences in property value growth since the early 1990s, reforms that meaningfully improve equity necessarily involve redistribution at the national level. In this sense, the counterfactuals examined here implicitly move toward a nationally integrated system of property taxation. This has important practical implications. Under the current framework, Council Tax is locally administered and forms a core component of local government funding, with rates adjusted by individual authorities. A nationally redistributive system would therefore require corresponding adjustments to funding arrangements, likely involving greater reliance on centralised transfers or block grants to ensure consistent service provision across regions.

Finally, this study demonstrates that large-scale statistical revaluation is feasible using publicly available data. By combining open datasets with modern machine learning techniques, it is possible to generate valuation estimates at a national scale that support meaningful policy analysis. While access to proprietary data would improve precision, the results show that transparent and reproducible methods can provide a credible basis for evaluating reform options. Future research could extend this work by incorporating political feasibility, examining interactions with the broader tax-benefit system, and improving data quality to refine both valuation models and policy simulations. Overall, the findings suggest that while structural reform matters, the primary driver of improved equity is the correction of outdated valuations. Once this is achieved, the central challenge becomes designing a system that balances proportionality, stability, and political feasibility.

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Appendix A: Additional Background and Policy

Early History and Original Design of the Council Tax System in 1993

To understand the misalignment between the current Council Tax and an optimal system that accounts for contemporary property values, it is essential to examine the current Council Tax's historical roots and the systems it replaced. The Council Tax was established in England in 1993 by the Local Government Finance Act of 1992 (Local Government Finance Act, 1992). It directly replaced the short-lived Community Charge, which had previously replaced the long-standing Domestic Rates system.

While the Domestic Rates system had existed in some format for centuries, the modern version of it was codified in England in the 1960s, though it continued to see reforms periodically. Under this system, properties were taxed based on their notional or assessed rental value. This framework ensured that property owners (or leaseholders)⁵¹ of higher-value homes paid a proportionately greater share of local taxes (Jones, Leishman, & Orr, 2006). While this approach established a direct connection between property wealth and tax liability, it faced criticism for placing a disproportionate burden on low-income households residing in high-value areas, particularly as property values grew in ways that did not consistently align with income levels. Additionally, the domestic rates system was criticised for placing the full burden of local taxation solely on property owners or leaseholders without accounting for the broader group of residents who also benefited from local services (Travers & Esposito, 2003; Jones, Leishman, & Orr, 2006).

⁵¹ Under the Domestic Rates system, the occupier was responsible for paying the domestic rates tax, though landlords often paid rates on behalf of tenants. Under the Council Tax system, similarly – when the owner is not the occupant – it is the occupier that is most often liable for Council Tax unless the property is a HMO or under certain other limited conditions.

In response to these challenges, the Community Charge, commonly known as the Poll Tax, was introduced in 1990⁵² under Prime Minister Margaret Thatcher. Northern Ireland elected to not adopt this new system but rather to amend and modernise the previous Domestic Rates tax. For the rest of the UK, the new structure imposed a flat-rate charge per adult resident within a local authority, irrespective of property value or individual income (Murdie & Moorhouse, 2021; Adam & Browne, A Survey of UK Tax System, 2006; Adam & Browne, Redistribution, Work Incentives and Thirty Years of UK Tax and Benefit Reform, 2010; Jones, Leishman, & Orr, 2006). The Community Charge system was originally designed to simplify tax collection and ensure uniform contributions from all residents, but it disproportionately impacted lower-income individuals by requiring them to pay the same amount as wealthier taxpayers. This inequitable approach led to widespread protests and tax resistance, resulting in significant political turmoil. In fact, many have attributed Thatcher's 1990 resignation to be related largely to the Community Charge, and senior figures within the Conservative Party, including Thatcher's successor John Major, distanced themselves from the policy (Adam & Browne, 2010; Jones, Leishman, & Orr, 2006; Murphy, Snelling, & Stirling, 2018).

Consequently, the Poll Tax was repealed and replaced by the Council Tax system, which was officially implemented in England, Scotland and Wales in 1993. Properties were assigned to one of eight valuation bands (A through H) based on their estimated market value as of April 1, 1991. Band D serves as the reference point for Council Tax, with fixed statutory multipliers applied to calculate liabilities for other bands (e.g., Band A paid 2/3 of Band D, while Band H paid 2x of Band D). [See Table 3.14.] All Councils were required to adopt this uniform banding structure, and although no statutory schedule for revaluation was established, it was generally assumed

⁵² The Community Charge was introduced in 1990 in England and Wales but in 1989 in Scotland.

that valuations would be updated periodically (approximately every 5 to 10 years) to reflect changes in the housing market.

From the outset, the Council Tax system combined local rate-setting with strong central oversight. While local authorities were responsible for setting the annual tax rate for Band D, they had no control over the relative multipliers or the 1991 valuation thresholds that defined each band, which were fixed in national legislation (Adam & Browne, A Survey of UK Tax System, 2006). Property assessments and band assignments were conducted centrally by the Valuation Office Agency (VOA), an executive agency of HM Revenue & Customs (HMRC), while local Councils managed billing and collection. Initially, Councils also faced central government controls over rate increases too. If a rate increase was deemed excessive by the Secretary of State, Council would be required to revise their budgets and set a lower rate.

In England and Wales, property valuations are carried out centrally by the VOA, who conducts the initial valuations for Council Tax by estimating each dwelling's hypothetical market value as of 1991 based on factors such as size, property type, location, and other characteristics (Valuation Office Agency, 2024). Initial assessments, which continue to underpin tax banding today, were conducted using desk-based mass appraisal techniques drawing on property transaction data from 1989 to 1991, rather than through individual property inspections of every dwelling (Giles & Ridge, 1993; Jones, Leishman, & Orr, 2006; Valuation Office Agency, 2024). The resulting valuation lists determine each property's band, and the VOA maintains and updates these lists as needed (such as when large structural changes are made). In Scotland, valuation responsibilities are administered independently by the Scottish Assessors Association (SAA), a body that operates outside the VOA framework (Adam, Phillips, & Ray-Chaudhuri, Scottish Council Tax: Ripe for Reform, 2025; Adam, Phillips, & Ray-Chaudhuri, Revaluation and Reform of Welsh Council Tax Should Proceed without Delay, 2023). Each local authority appoints an Assessor (or Deputy Assessor) to determine band assignments, introducing some regional variation in assessment methodologies (Murdie & Moorhouse, 2021; Alma Economics, 2023). This was not a divergence

from the English model, but rather the continuation of a distinct institutional structure that predated the introduction of Council Tax.

The Local Government Finance Report (England) 1993–94 was issued alongside the establishment of Council Tax. This retained the Standard Spending Assessment (SSA) formula to allocate general revenue support grants. This framework ensured that Councils with weaker tax bases, often those with large shares of Band A and B properties, received sufficient central government support to deliver comparable services without imposing disproportionately high Council Tax rates (Giles & Ridge, 1993). The Local Government Finance Settlement, issued annually, outlines the distribution of these formula-based grants in England, including allocations from the Revenue Support Grant, redistributed business rates, and police grants, collectively known as the Formula Grant (Communities and Local Government, 2009). These equalisation mechanisms aim to address disparities in local tax capacity and service needs, allowing less affluent Councils to maintain essential services while wealthier areas receive comparatively less aid.

Additionally, to protect low-income households, the government implemented Council Tax Benefit (CTB), a centrally funded, means-tested support scheme that could cover up to 100% of a household's Council Tax liability. Finally, the Local Government Finance Act of 1992 also established several discounts and exemptions that largely remain in place today. Unlike CTB, these are not means-tested but rather applied to certain protected classes. Sometimes referred to as Council Tax Discounts & Exemptions (CTDE), these programs are standardised and implemented by the central government, meaning that they apply equally to all Councils. Among these is the Single Adult Discount (which reduces the payable amount by 25% for households with only one adult) and the 50% reduction for vacant properties. By far, the Single Adult Discount is the most impactful and controversial reduction. It applies to roughly 8.41 million of the 25.68 million chargeable dwellings in England, effectively reducing total Council Tax revenue by approximately 8.2% (Ministry of Housing, Communities & Local Government, 2025). Proponents argue it provides necessary relief for single-occupant households who do

not consume as many resources and would otherwise bear the full cost of a property-based tax; on the other hand, critics contend that it undermines the tax base by granting a blanket reduction regardless of income or property value. Additionally, opponents argue that it discourages efficient use of the housing stock by disincentivizing household consolidation, particularly in areas with constrained housing supply such as London.⁵³

Beyond these discounts, full or partial exemptions for properties that are occupied solely by those with severe handicaps, full-time students, and those serving in the armed forces exist under CTDE. For many of these exemptions, the number of occupants are decreases and thus the liability is decreased⁵⁴ (Department for Levelling Up, Housing & Communities, 2024; Murdie & Moorhouse, 2021; Adam & Browne, Reforming Council Tax Benefits: IFS Commentary C123, 2012; Office for Budget Responsibility, 2024; Valuation Tribunal Service, 2013). Finally, there are situations where premiums can be applied, increasing tax liabilities above the standard rate. The most notable premium is the one placed on second homes, which can as much as double Council Tax liabilities (Ministry of Housing, Communities & Local Government, 2025).

International Comparison of Property Tax Systems

In contrast to the United Kingdom, many countries have adopted more dynamic property tax systems. Denmark and Sweden, for instance, routinely conduct market-based property valuations. This is similarly done in France, Germany, Canada, and the United States, though reassessment frequency varies by jurisdiction (Slack & Bird, 2014; OECD, 2022). Additionally, some provinces in Canada (namely Ontario) and the United States have

⁵³ In other high-density markets, policy has targeting increasing densification; for example, in Sanghai and Chongqing, a property tax pilot was shown to be effective in restricting multiple properties or oversized homes. In *Property Taxes and Growth Patterns in China* (2022) by Zhang and Lin, a strong increase in total factor productivity (TFP) and a reduction in property prices was found as a result of this pilot.

⁵⁴ For a vacant property to be fully exempt from Council Tax, certain criteria must be met. These include situations where the owner is in a care facility, a charitable organization owns the property, the owner is deceased, the property is owned by a pastor, the owner is imprisoned, or other specific cases (Murdie & Moorhouse, 2021; Citizens Advice, 2020).

increasingly implemented Automated Valuation Models (AVMs) to enhance valuation accuracy and efficiency (Bidanset & Rakow, 2022). While AVMs entail higher initial administrative costs, empirical evidence suggests that they significantly improve revenue efficiency by ensuring assessments remain aligned with market conditions.

Beyond reassessment frequency and valuation methods, many countries also differ from the UK in their tax rate structures. Rather than relying on rigid bands, jurisdictions such as Canada and several U.S. states apply a flat mill rate⁵⁵, where tax liabilities are determined as a fixed percentage of assessed property values (Slack & Bird, 2014; OECD, 2022). This ensures that all properties contribute proportionally, allowing higher-value properties to generate more revenue without distorting tax neutrality. Other regions, including France and certain U.S. states, employ progressive property tax systems where tax rates increase with rising property values, ensuring that wealthier property owners contribute a higher percentage of their assessed value (Hinders, 2024). These models stand in stark contrast to the UK's static banding system, where high-value properties often shoulder disproportionately low tax burdens relative to their market values.

Still, there are a few countries that utilise banding systems like the UK, such as Ireland, South Korea, and Singapore. These systems, however, allow for more frequent revaluations and scale tax liability more directly and proportionally with property value, especially at the upper end. International examples not only demonstrate the feasibility of reform but also highlight the potential for greater administrative efficiency and revenue stability.

⁵⁵ California is a notable exception due to Proposition 13, which caps both tax rates and value reassessments. While popular with many homeowners, it is increasingly criticized by economists and policy analysts for distorting markets, reducing equity, and undermining local public finance.

The Transition from the Council Tax Benefit to the Council Tax Relief Scheme in Scotland and Wales in 2012

Following the Welfare Reform Act 2012, which repealed and replaced the Council Tax Benefits (CTB) with Council Tax Relief (CTR), England elected to larger permit Councils to administer CTR independently (including determining eligibility). Comparatively, Scotland and Wales retained a more centralised system with the central governments continuing to fund a nationally consistent CTR scheme. (Ayrton, Holden, & Kenway, 2022). Wales elected to adopt the same 10% reduction in funding that England had, and the Scottish Government fully offset the funding shortfall, maintaining funding at the same level as CTB (Adam & Browne, 2012; House of Commons Library, 2012). Central control resulted in greater protection for low-income households in Scotland and Wales. England also experienced more turbulence handling the funding reduction, managing and balancing the diversity of CTR schemes, and later adjusting CTR based on changes to households' Universal Credit (UC) coverage⁵⁶ (Ayrton, Holden, & Kenway, 2022; The Council Tax Reduction Schemes (Prescribed Requirements) (England) Regulations, 2012). The variability in CTR schemes specifically led to increased financial strain for some vulnerable groups, rising arrears, and administrative challenges for local authorities struggling to balance reduced budgets with the need to support residents. In turn, this led to some local authorities facing budget constraints, administrative challenges, and reduced levels of support ultimately resulting in increased financial pressures on low-income households. Subsequent statutory instruments have sought to address some of these concerns by shaping a relief framework. For instance, the 2012 Council Tax Reduction Schemes set out mandatory criteria

⁵⁶ Notably there is a close relationship between CTR and Universal Credit. Universal Credit, which was also piloted in 2013, before expanding across the UK, doesn't directly impact Council Tax, but it replaced several means-tested social welfare benefits, including Income-based Jobseeker's Allowance (JSA)), Income-related Employment and Support Allowance (ESA), Income Support, Working Tax Credit, Child Tax Credit, and most notably, Housing Benefits. However, when Housing Benefit was rolled into Universal Credit, this removed a single application process for both rent and Council Tax help in many areas, creating administrative complexity. Claimants must now apply for Council Tax Reduction separately from Universal Credit, which has led to concerns about reduced uptake of Council Tax support and increased arrears among low-income households. A 2020 report by researchers with the Welsh government concluded that there were fewer CTR awards and more council tax arrears because of the Universal Credit system in Wales (Aston, et al., 2020).

that local systems must adhere to, ensuring a degree of consistency in the support provided to vulnerable groups (The Council Tax Reduction Schemes (Prescribed Requirements) (England) Regulations, 2012). To address these (and other challenges) with the CTR system in England, three fundamental changes have occurred over the past decade. First, a minimum payment for all properties, regardless of CTR, was established. Second, CTR limits for the higher bands were set up (where the limit is based on the maximum CTR for the lower bands). Third, an income bands scheme was developed; this is an adjustment to the previous system in that it allows for some flexibility in income expansion without reducing CTR (Ayrton, Holden, & Kenway, 2022).

Council Tax Support (CTS) System Design and Take-Up Challenges

Although CST softens the regressive bias introduced by using antiquated values, it does not remove it. Because valuations are frozen at 1991 levels, detailed assessment data is not publicly available, and CTR interacts with liability calculations, isolating the precise impact is difficult. Nevertheless, the evidence (and our own analysis later in this study) shows that owners of lower-value homes still pay a significantly higher effective tax rate relative to market value. Even if CTR was sufficient to provide a fair system of taxation, CTR take-up rates are only a portion of those that are eligible (Jones, Leishman, & Orr, 2006; Murphy, Snelling, & Stirling, 2018). Though a conclusive figure is not available, most estimates are that take-up rates are between 60% and 70%, meaning that about 1/3 of the eligible population is not receiving CTR. This represents as much as £3.5 billion in unclaimed benefits (Bahia & Walker, 2025; Smitherman, 2024). In part, low take-up rates can be attributed to the fact that CTR requires a separate application and is administered independently of Council Tax and Universal Credit. The process is also complicated where properties often need to be reassessed (sometimes multiple times), which leads to claimants dropping claims (Bahia & Walker, 2025).⁵⁷

⁵⁷CTR take-up rates are decreasing, though Trust for London claims that a recently funded project with Policy in Practice yielding some exploration into automated council tax support by at least some Councils (Trust for London, 2025).

The complexity of CTS has fueled discussions on whether CTS should be replaced with more automatic mechanisms that avoid the need for individuals to proactively claim them. One of the most discussed reforms is integrating means testing directly into council tax liability, eliminating the need for separate applications. Proponents argue that an automatic, income-based system would remove stigma and ensure that relief reaches those who need it. Several policy proposals suggest replacing or supplementing the current system with income-based taxation, either as a full local income tax (as once proposed by the Liberal Democrats) or through hybrid models where income caps an individual's tax liability. Hybrid models have gained traction, as they retain a property-based component while addressing concerns about households that are property-rich but income-poor, such as pensioners with high-value homes but limited cash flow. Internationally, circuit breakers in the U.S. provide rebates when property taxes exceed a certain share of income, while countries like Sweden and Denmark rely on local income taxation rather than high property taxes. These approaches demonstrate that income-sensitive local taxation is feasible, though implementing such a system in England would require extensive coordination with HMRC and local authorities, raising questions of political feasibility and administrative complexity.

Still, while the fragmentation through localised design of CTR complicates enrolment and thus take-up rates, even under the centralised CTB, there was not a perfect relationship between income and Council Tax reprieve; for example, Adam and Browne (2012) noted that the lowest income decile only qualified for CTB 38% of the time, while qualification was 46% and 44% for the second and third poorest deciles (Adam & Browne, 2012; Murphy, Snelling, & Stirling, 2018). Additionally, another study conducted during the transition from CTB to CTR found that those in lower bands only accessed about 2/3 of the provisioned relief funds (Adam & Browne, *Reforming Council Tax Benefits: IFS Commentary C123*, 2012). Beyond take-up rates, over 70% of local authorities currently have a minimum payment requirement (Rose, 2023). Combined with the fact that local CTR schemes are a patchwork of uniquely designed and administered system, a “postcode lottery” in support outcomes has been created (Rose, 2023; PLMR, 2023). These limitations underscore the need for fundamental reform

through revaluation and band restructuring to ensure a fairer distribution of tax burdens. The following section will explore these reforms deeper.

Geographic and Structural Distortions from Outdated Valuations

Among the necessary fiscal reforms, updating property valuations remains an imperative priority. The failure to conduct regular revaluations has resulted in significant inequities, revenue inefficiencies, and administrative complexities. The existing valuation framework fails to reflect contemporary market conditions, thereby exacerbating economic disparities. As highlighted by Avenancio-Leon and Howard (2022), the misalignment between assessed property values and actual market prices distorts economic incentives (potentially encouraging speculative behavior and exacerbating supply-demand imbalances) and contributes to inefficient resource allocation. Their findings indicate that properties in certain demographic areas are systematically undervalued relative to their true market worth, leading to a misapplication of tax burdens that do not correspond with underlying economic fundamental (Avenancio-Leon & Howard, 2022).

Disparities in the Council Tax system are primarily driven by uneven property value appreciation since 1991. As noted prior, property price growth in the south of England, and especially in and around London, has significantly outpaced that of northern England (Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020; ONS, 2024; Avenancio-Leon & Howard, 2022; Xu, Phillips, Hodge, & Adam, 2020). As illustrated in [Figure 3.9](#), property prices in London have increased by approximately 5.9 times their 1991 levels by 2023, whereas property values in northern England and the Midlands have risen by only a 3.5 multiple (ONS, 2024). Even amongst more localised areas, property price growth has a high variance. Across all local authorities, average prices ranged from 98% to 778% their 1993-94 rate in 2023. The majority (second to third quartiles) of changes range between 1.6 and 5.6 times the starting value. Furthermore, the long-term liability increases have had little correlation with the property price changes meaning that as prices have grown, local authorities' changes in the tax rate have fluctuated disproportionately to the price inflation.

At a Council level, London has experienced one of the lowest and most consistent rates increases despite the property price growth (UK.gov, 2024). Similarly, while London's higher average Band D charge is broadly in line with its elevated property prices, the pattern does not hold elsewhere; across the remaining regions, liabilities show little correlation with underlying property values. Using average housing prices published by the Ministry of Housing, Communities & Local Government and the VOA's band D liabilities, the correlation between property values and council tax liabilities in 2023 was relatively weak, with a Pearson coefficient of 0.4133 across local authorities. Long-term trends suggest that Councils do not adjust Band D charges to keep pace with relative property-price appreciation, reinforcing the disconnect between tax burdens and market dynamics. In practice, this means that geographic disparities in tax burden occur even between properties that have similar contemporary values and are taxed in the same band.

A similar pattern extends to the relationship between liabilities and socio-economic factors such as income and deprivation. Across local authority districts, the correlation between Band D liabilities and deprivation scores is only 0.1235, suggesting that liabilities do not systematically adjust to local economic conditions. This misalignment results from the devolved structure of rate-setting where each Council sets its precept independently. They are balancing local service demands and political constraints against their own revenue base. Localities are not homogeneous, and variations in income, housing stock, and deprivation across jurisdictions therefore drive Council decisions, leading them to prioritise fiscal sufficiency over a uniform market-based tax structure.

The regional inequities are not localised to England. Evidence from Wales illustrates the scale of distortions caused by outdated valuations. In Adam, Hodge, Phillips & Xu (2020), it is demonstrated that revaluation in Wales, had it been conducted, would have led to a substantial reshuffling of properties across bands, given significant disparities in property value growth since 2003. The authors confirm that properties in lower-value areas have, in many cases, appreciated at a slower rate than those in wealthier regions, yet they remain

locked into disproportionately high tax burdens. The lack of periodic revaluations has also led to inefficiencies in revenue collection, with some local authorities losing tax revenue due to properties being undervalued relative to their current market position. Furthermore, the outdated valuation basis has widened regional inequities, particularly disadvantaging households in economically stagnant areas that have not experienced the same capital appreciation as high-growth regions (Adam, Hodge, Phillips, & Xu, Revaluation and Reform of Council Tax in Wales, Impacts on Different Council and Household Types, 2020). The Welsh case serves as a strong parallel to England, where valuation dates are even older and retail property price growth inequality has been even more pronounced, exacerbating these same inequities on a national scale.

Beyond regional inflation disparities, there are several other compelling reasons to update property valuations. First, even within smaller geographic areas, price appreciation has not occurred evenly. Lower-income communities or specific property types, particularly flats and ex-social housing, have often seen far slower growth than wealthier neighborhoods or detached homes. For example, in London, stark disparities in localised house price inflation have been observed, undermining the assumption that historical valuations remain equally outdated for all properties (Murphy, Snelling, & Stirling, 2018). Second, aligning tax liabilities with actual market conditions can improve the fairness and efficiency of service funding. When liabilities better track real property values, Councils are better equipped to generate revenue in proportion to residents' ability to pay, ensuring that those who benefit more from rising house prices contribute appropriately to public services. This rebalancing is particularly important as the gap between low- and high-value properties has again widened considerably even within small geographic areas over the past three decades (Adam, Phillips, & Ray-Chaudhuri, 2025). Third, improved valuation methodologies would yield administrative benefits, especially in managing new developments. Newly constructed properties are currently assigned speculative 1991-equivalent values, a process that becomes increasingly unreliable as historical comparable disappear, further undermining consistency in tax administration. Fourth, proponents of revaluation often note its potential to modestly increase revenues, though this is likely based on the structure of the revaluation and the updates made to bands as a result. In Wales, for

example, the 2005 revaluation resulted in a marginal net increase in overall Council Tax receipts. However, much of this increase was attributable to the introduction of a new top-tier Band I rather than reassessment alone (Adam, Phillips, & Ray-Chaudhuri, 2023). More broadly, while some studies suggest that modernised valuations can enhance local government revenue, this is not a guaranteed outcome. As Adam, Hodge, Phillips, and Xu (2020) argue, the fiscal impact of revaluation is highly context-dependent, varying with regional housing market conditions and local tax-setting behavior. Even in the absence of additional revenue, reforming outdated valuations can yield substantial gains in legitimacy, transparency, and perceived fairness by making tax burdens more proportionate to current property values (OECD, 2022; Slack & Bird, 2014).

In this regard, a major weakness of the current system lies in its opacity. Homeowners typically cannot access the 1991 valuation used to assign their tax band; only the band designation itself is disclosed. This lack of transparency limits public understanding of how Council Tax liabilities are determined and hampers opportunities for empirical evaluation of the system's distributional impacts. As shown in Figure 3.4, tax liabilities as a share of property value decline markedly across the bands, contributing to a regressive burden that is difficult for taxpayers to verify or contest. The inaccessibility of valuation data has likely contributed to the low number of households challenging their band placement, despite the potential for widespread misclassification. Calls for greater access to valuation data and improved taxpayer information services have grown in recent years, particularly as the need for reform becomes more evident (Welsh Government, 2022). Moreover, a modern revaluation would not only improve accuracy but also enhance transparency by allowing taxpayers to more clearly see how their liabilities relate to current property values. This would strengthen public trust in the fairness and consistency of the system.

The adoption of updated valuation methodologies can help mitigate these distortions by ensuring more equitable tax liabilities across regions, income groups, and property types. When accurately levied, property taxes can serve as a key tool for promoting fiscal stability and improving the distribution of tax burdens (Hou, Ding,

Schwegman, & Barca, 2021). In Eom (2008), frequent reassessment was shown to have a positive relationship with assessment uniformity. The author concluded that each year of lag could result in a 1.6% decline in assessment uniformity, implying that market-based models would likely lead to fewer assessment discrepancies. These findings reinforce the importance of regular revaluation cycles for ensuring a more equitable and credible property tax system.

Regressive Effects of the Current Banding Structure

Beyond need for updated valuations, the structure of the Council Tax banding system has come under sustained criticism for its regressive effects. Rather than levying tax as a percentage of property value, the system assigns properties to fixed bands, resulting in an Effective Tax Rate (ETR) that declines as property values rise. This pattern is evident at the local authority level but also observable nationally. On average, Band H properties incur a liability roughly three times greater than Band A properties, despite the fact that Band H thresholds represent at least eight times the property value of Band A. As a result, higher-value properties often benefit from proportionally lower tax liabilities, despite owners frequently holding overall wealth far exceeding the value of their primary residences (Adam, Hodge, Phillips, & Xu, 2020). Again, the Welsh experience offers a valuable reference point. In their study of the 2005 Welsh revaluation, Adam et al. (2020) found that the banded structure reinforced regressivity, with wealthy households continuing to pay a smaller share of property value in tax even after the reform. The study also highlights how means-tested relief mechanisms, such as Council Tax Reduction (CTR), complicate the assessment of equity, as they partially mitigate burdens for low-income households without altering the fundamental regressivity of the underlying tax structure. Consequently, criticisms of Council Tax have increasingly focused not only on outdated valuations, but also on the design of the band system itself (Adam, Hodge, Phillips, & Xu, Revaluation and Reform of Council Tax in Wales, Impacts on Different Council and Household Types, 2020).

In addition to the regressive relationship within the bands, concerns have been raised regarding the broad valuation ranges within each tax band. First, particular concern regarding the capped liabilities for the top band garner most of the attention. Although only a small fraction of properties (approximately 0.6%) are classified within the highest tax band (Band H), the range of property values within this category is exceptionally wide (VOA, 2021). In practice, this discrepancy is even more pronounced, particularly in high-value areas such as London, Cambridge, Oxford, and Bristol, where Band H properties may be worth twenty or more times as much as Band A dwellings, yet face relatively modest differences in tax liability (Adam, Hodge, Phillips, & Xu, *Revaluation and Reform: Bringing Council Tax in England into the 21st Century*, 2020). While this pattern is not uniform across all bands and jurisdictions and it is counterbalanced by means-tested CTR, prior studies agree that the system is regressive, taxing lower bands at higher relative rates to the properties' values broadly across the UK (FitzRoy & Jin, 2021; Adam, Hodge, Phillips, & Xu, *Revaluation and Reform: Bringing Council Tax in England into the 21st Century*, 2020; Alma Economics, 2023; The Commission on Local Tax Reform, 2015). This was the motivation for Wales adding a ninth band in 2005, and Scotland has frequently explored a similar policy change.

In addition to the top band, concerns have been raised regarding the broad valuation ranges within the lower bands as well. Critics argue that this design disproportionately burdens homeowners whose properties are valued near the lower threshold of their assigned band. In such cases, households may face a higher effective tax rate relative to property value, despite residing in homes that are considerably less valuable than others within the same band. This results in a form of horizontal inequity, where households with different levels of property wealth are subject to the same tax liability. Like many challenges to the banding design, the problem is further intensified by the outdated nature of the underlying property valuations, as often neighboring properties might fall into the same band but have real valuation that are even wider than the band ranges.

Finally, while band ratios and property assessments are standardised by the Valuation Office Agency (VOA), local Councils retain discretion over annual tax rate adjustments and overall liability determinations. This division of responsibilities has raised concerns regarding the potential for widening regional fiscal disparities. Research has shown that economically disadvantaged areas often hesitate to increase tax rates due to concerns about the financial burden on lower-income households (Bellofatto & Besfamille, 2021; Muldoon-Smith & Greenhalgh, 2015). However, this reluctance can create a self-reinforcing cycle of underinvestment, as Councils in lower-value property regions face revenue constraints that limit their ability to fund essential public services, such as healthcare, emergency response, and infrastructure development. As a result, these regions struggle to attract new investment or improve living conditions, further entrenching economic disparities (Bellofatto & Besfamille, 2021).

Advantages of Automated Valuation Models

From an economic perspective, ML-driven AVMs offer clear advantages in cost-effectiveness, speed, and objectivity. As the IAAO standard notes, once established, AVMs impose very low marginal costs for additional assessments and enable rapid processing of large datasets, making frequent revaluations feasible within constrained administrative budgets (International Association of Assessing Officers, 2023). Additionally, studies have shown that AVMs improve consistency by applying standardised algorithms, thus removing idiosyncratic human judgment from valuations (RICS, 2022). This consistency stems from the model's ability to incorporate local fixed effects while simultaneously leveraging broader market trends, allowing it to generate valuations that are both locally sensitive but considerate of national trends. This not only ensures more equitable tax assessments but also frees up the labor force (namely assessors) to focus on quality control and complex cases rather than routine valuations. While automated models have been considered, most researchers have concentrated on manual and periodic revaluation. While automated models might enable semi-real time appraisal and thus annual tax

changes, longer cycles might ensure more stability and reliability for homeowners. Additionally, it would reduce the impacts of demand and price shocks, enabling valuations to be based on multi-year weightings.

In fact, many studies have found that AVMs, with the ongoing integration of better data and improving ML algorithms offer a significant advantage over traditional statistical models and are continually improving (Ho, Tang, & Wong, 2021; Mu, Wu, & Zhang, 2014). For example, an early study by Mu, Wu & Zhang (2014) compared non-linear learning methods to a standard regression and showed that support vector machines (SVM) and least-squares SVM (LSSVM) produced the best forecasting accuracy for housing values (Mu, Wu, & Zhang, 2014). Later, Ho et al. (2021) applied support vector machines (SVM), Random Forest (RF), and gradient boosting (GBM) to over 40 thousand Hong Kong transactions; they found that RF and GBM achieved substantially lower valuation errors – as measured by the Mean-Squared Error (MSE), Root Mean-Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) – compared to SVM. The authors conclude that machine learning “offers a promising, alternative technique in property valuation” for price prediction that yields fairer and more uniform tax assessment while reducing the need for human appraisers (Ho, Tang, & Wong, 2021). The usefulness of Random Forest as a prediction algorithm is also found in Koktashev et al. (2019), which similarly finds that RF estimates property prices with an 8% error (Koktashev, Makeev, Shchepin, Peresunko, & Tynchenko, 2019).

Although the initial implementation cost, such as developing technical infrastructure, acquiring high-quality data, and training personnel, can be substantial, these fixed investments are offset over time by operational efficiencies and enhanced revenue stability. In fact, cost reduction and the benefits of economies of scale is often a driving factor behind adoption of AVMs (RICS, 2022). The marginal cost of revaluation decreases as AVMs scale, enabling jurisdictions to update assessments more frequently without proportionally increasing administrative burden. As adoption grows, network effects further strengthen model performance by expanding available training data and institutional expertise, reinforcing both valuation quality and system resilience. Case studies and country-specific pilots reinforce these efficiency gains. According to Demirci (2021), machine-

learning AVMs can reduce valuation errors to single-digit percentages and significantly lower staffing needs compared to traditional in-person assessment methods. Whether conducted through manual inspection or automated modelling, regular reassessment is a foundational prerequisite for any meaningful reform to Council Tax. Without accurate, up-to-date valuations, changes to band thresholds or tax rates risk reinforcing existing inequities rather than resolving them.

Political Feasibility and Public Sentiment of Council Tax Reform

The political feasibility of reforming the Council Tax system is a complex issue, shaped by both historical resistance to property tax adjustments and prevailing public sentiment. The Welsh Government's *A Fairer Council Tax Consultation* (2022) underscores these challenges, revealing both a recognition of the need for reform and a substantial reluctance to accept certain changes, particularly property revaluations (Welsh Government, 2022; Plimmer, McCluskey, & Connellan, 1999). The consultation surveyed 949 Welsh citizens and 75 additional stakeholders to gauge public opinion on potential Council Tax modifications. As summarised in Table 3.15, a majority of respondents opposed a 2025 property revaluation, as well as periodic revaluations every five years. However, a slight majority expressed support for adding new tax bands and refitting the existing bands, signaling a preference for incremental rather than systemic reform. Written responses also indicated a desire for greater transparency in the system, with some respondents advocating for alternative approaches to property taxation (Welsh Government, 2022).

In addition to the survey conducted in Wales, a similar study was conducted in Scotland in 2023 with 15,628 respondents. This study proposed adjustments to the 2017 increases, specifically 7.5%, 12.5%, 17.5%, and 22.5% for Bands E, F, G, and H respectively. Most respondents expressed opposition to these increase levels, citing concerns about fairness and the impact on financial and mental well-being. Only 3% of respondents supported the proposed rates, and merely 4% were in favour of any increases (Alma Economics, 2023). However, it is

important to note that this survey had a significant bias towards respondents from higher bands; 91.4% of respondents who identified their bands were from Bands E-H, even though most households fall below Band D.

These findings align with broader trends in public opposition to property tax changes, often driven by concerns over increased financial burdens and uncertainty regarding future tax liabilities. Notably, survey respondents also expressed resistance to reassessing properties following significant home improvements, reflecting a concern that such reforms might disincentivise property investment. This hesitancy complicates efforts to modernise the Council Tax system, as any adjustments to banding or valuation methodologies may be met with skepticism from homeowners who fear unintended financial consequences. Similar challenges have stalled prior attempts at reforming property taxation in the UK, as public opposition and administrative complexities contribute to political inertia, even when economic rationale supports reform.

One of the key obstacles in reforming the banding system is the entrenched nature of the existing structure. Unlike a full-scale revaluation, which recalibrates the entire property tax base, adjusting tax bands represents a more targeted intervention that can mitigate extreme regressivity without fundamentally disrupting the system. The survey results suggest that while revaluation remains a politically contentious issue, band reform, such as the introduction of new bands at the upper and lower ends of the scale, commands relatively greater public support. This suggests that policymakers may find banding adjustments more viable as an initial step toward broader reform efforts. However, even banding reforms are not without challenges; determining appropriate thresholds for new bands and addressing regional disparities in property values require careful consideration to avoid unintended distortions in tax liabilities.

The *A Fairer Council Tax Consultation* survey itself, while informative, must be interpreted with caution due to potential selection and response biases. While the survey sample size selection isn't published, it is slightly below the standard threshold required for a 3% margin of error at a 95% confidence interval for Wales' population of approximately 3.3 million (the minimum for this threshold would be 1,068 respondents). Additionally, public

sentiment reflected in the survey may not fully capture the broader population's preferences, particularly given the potential for response bias in voluntary consultations. Moreover, attitudes in Wales may not directly translate to England, where socioeconomic and regional variations could shape different perspectives on tax reform. Despite these limitations, the consultation provides valuable insights into public attitudes toward property taxation and the potential pathways for politically feasible reform.

Beyond political challenges, technological advancements present an opportunity to modernise property tax assessments in a manner that minimises taxpayer resistance. Automated Valuation Models (AVMs) could mitigate some of the administrative and political hurdles associated with revaluation by offering a more continuous, data-driven approach to property valuation. These models, leveraging machine learning techniques and geospatial data, have demonstrated strong predictive accuracy in real estate valuation contexts. By enabling more frequent and less intrusive property assessments, AVMs could help maintain valuation accuracy without necessitating large-scale, labor-intensive reassessments. While the adoption of AVMs alone may not resolve concerns surrounding tax banding and regressivity, they represent a significant step toward improving the fairness and efficiency of property taxation while addressing some of the public's apprehensions regarding tax reform.

Despite the political and administrative barriers to reform, there are compelling counterarguments that suggest a greater openness to change than is often assumed. While revaluation or band adjustments would inevitably create winners and losers, the potential benefits for many households, particularly in the North of England, could make reform more politically viable. Given regional disparities in property values, areas that have seen slower price appreciation since 1991 may experience tax reductions under a more current and equitable system. Conversely, households in the South, particularly in London, where property values have far outpaced Council Tax liabilities, might see increases in tax burdens. In *Revaluation and Reform: Brining Council Tax in England into the 21st Century* (Adam et al. 2020) suggest that the Midlands and the northern regions would likely see total tax decrease by roughly 20%, and while that would be offset by tax increases in other regions, more

households would benefit from reforms than would be negatively impacted. The authors estimate that 24% would see annual bills fall by £200 or more, while only 4% would experience increases in their annual liabilities by £200 or more. This too could be mitigated with greater investment in CTR and central government support (Adam, Hodge, Phillips, & Xu, 2020). Additionally, the long-term fiscal benefits, such as increased revenue stability and more equitable resource distribution—could help mitigate the most severe impacts, especially for lower-income households or those with relatively affordable primary residences. A well-structured reform could incorporate exemptions, transitional relief, or means-tested adjustments to ensure that the tax burden does not disproportionately fall on economically vulnerable homeowners. Furthermore, as property taxation becomes increasingly disconnected from actual market values over time, the perceived unfairness of the system may itself generate a stronger push for change. If future reforms are framed not merely as tax increases but as a rebalancing effort to create a fairer and more transparent system, public resistance may soften, especially if adjustments are phased in gradually to limit abrupt financial shocks.

Implementation Considerations and Mechanisms for Council Tax Reform

Many of the proposed reforms to the Council Tax systems (namely the banding structure) explore a transitional reform, in which large changes in bands are accompanied with a multi-year shift in tax liabilities. Because a transitional period could temporarily reduce revenue (depending on the design) by deferring higher liabilities for households facing increases, two main proposals have emerged to address the fiscal cost of providing transitional relief. First, a simultaneously phase-in, where households with rate increases *and* decreases both phase in over multiple years would be self-funding, as initial overpayments by “winners” would offset the underpayments by “losers”. However, this comes at the cost of immediately reducing rates for those that have the highest need and have experienced the least relative growth since 1991. As an alternative solution would be that central government can provide an explicit grant to local authorities to cover the revenue shortfall from capping bills (Adam, Hodge, Phillips, & Xu, *Revaluation and Reform: Bringing Council Tax in England into the 21st Century*, 2020; Xu,

Phillips, Hodge, & Adam, 2020; Xu, Phillips, Hodge, & Adam, 2020). Additionally, transitional relief schemes are a widely recommended tool to cushion sudden increases in tax bills for those in properties that see large valuation jumps. This involves phasing in rises over several years – for example, capping annual bill increases to a certain percentage or allowing properties that move up multiple bands to be taxed as if they moved up only one band per year. Such a scheme was used when Wales revalued in 2005, where households facing big increases had their rises limited and spread over time (Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020; Adam, Hodge, Phillips, & Xu, Revaluation and Reform of Council Tax in Wales, Impacts on Different Council and Household Types, 2020; Xu, Phillips, Hodge, & Adam, 2020). Either way, phasing gives households time to adjust to higher bills before the full liability takes effect. There is a trade-off, however, since complex transitional arrangements add administrative overhead and delay full implementation of the new equitable structure.

Even with phasing, some Councils could experience changes in their overall tax base after revaluation; areas where property values have grown far above the national average would collect more revenue at unchanged tax rates, while low-growth areas would collect less. Policymakers, both at the local and national levels, therefore, must decide how to administer inter-governmental finances to avoid offsetting the gains from a reduction in households' tax burdens by regional budget pressures resulting from the tax cut. One options would be to reallocate central government grants or recalibrate equalization mechanisms in tandem with the tax reform so that Councils with relatively lower tax capacity (e.g. areas that were historically over-taxed relative to new values) can afford to reduce average bills, while high-property-value areas might see higher average contributions (Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020). If central funding is adjusted in this way, the reform could achieve a geographic rebalance of tax burdens. For example, making Council Tax proportional to up-to-date values could substantially reduce average bills in much of the North and Midlands and increase them in London. However, it should be noted that, because Councils control the band D rate, revenue neutrality is not necessarily guaranteed. Still, revenue neutrality in reforms has

been the express goal in other restructuring efforts, such as the recent Welsh reforms (Adam, Phillips, & Ray-Chaudhuri, Revaluation and Reform of Welsh Council Tax Should Proceed without Delay, 2023). In practice, a balance can be struck: the reform package could be broadly revenue-neutral nationally (to satisfy fiscal constraints) but allow some redistribution across Councils and leave intact the local discretion for authorities to set their own tax rate. Local governments would thus retain autonomy to adjust rates (within any limits set by central government), ensuring they can still reflect local service needs and preferences even under a reformed system.

Finally, implementing Council Tax reform would entail measures to protect vulnerable and low-income households from undue hardship. CTR reform is complex and adapting these schemes to the new valuation base and band structure so that those least able to pay do not see net increases is a principal goal of most proposals. For low-income individuals facing rate increases, some argue that local governments could expand CTR schemes and eligibility, offsetting any Council Tax hike for low-income residents. Evidence suggests that making Council Tax more proportional to property values would, on the whole, benefit lower-income households (many in cheaper homes would see bill reductions) and relatively few low-income households would face large increases, since many receive CTR already (Adam, Hodge, Phillips, & Xu, Revaluation and Reform: Bringing Council Tax in England into the 21st Century, 2020). Either way, targeted support is vital for that minority who might be “asset-rich but cash-poor,” such as elderly individuals on modest incomes living in high-value homes (Adam, Phillips, & Ray-Chaudhuri, 2025; Adam, Phillips, & Ray-Chaudhuri, Revaluation and Reform of Welsh Council Tax Should Proceed without Delay, 2023). Another commonly proposed mechanism for these situations is a deferral scheme, allowing certain households to defer payment of part of their Council Tax until a later date, such as when the property is sold or upon the owner's death. This deferral acts as a government loan of the tax liability. To prevent potential misuse and revenue loss, such schemes typically charge interest on deferred amounts, as seen in Ireland and parts of Canada, ensuring that only those who are genuinely cash-poor would opt to defer. Scotland, for example, has considered both enhanced CTR and deferrals; a recent consultation on council tax reform

proposed increasing relief for low-income households and exploring deferral options for homeowners unable to pay higher bills (Adam, Phillips, & Ray-Chaudhuri, Scottish Council Tax: Ripe for Reform, 2025).

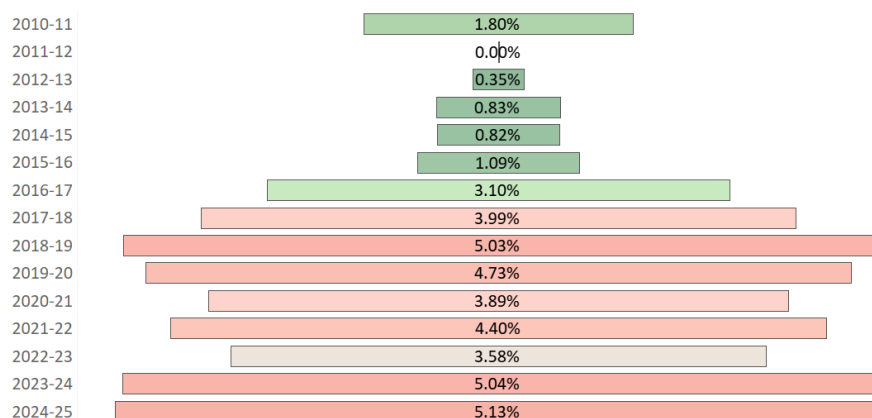
While there are many proposals for implementing Council Tax reform, a combination of measures, such as regular revaluations, phased implementation with transitional relief, adjusted funding between central and local government, and strengthened relief or deferral programs, could help transition to a reformed Council Tax system in England. These strategies aim to balance equity and political feasibility by aligning liabilities more closely with current property values and taxpayers' ability to pay, while preserving revenue stability for local authorities and mitigating regressive impacts. However, research from the Welsh Government indicates that even substantial reform is unlikely to produce dramatic shifts in average Council Tax liabilities or aggregate revenue, suggesting limited fiscal elasticity within the existing structure (Welsh Government, 2021). As inflationary pressures and statutory service obligations increase, maintaining fiscal sustainability may require broader reforms to the intergovernmental funding model, including reassessment of the relative weight of centrally allocated grants versus locally raised revenues.

Appendix B: Additional Figures and Tables

Table 3.14: Tax Bands and Property Valuation Ranges by Country and Band

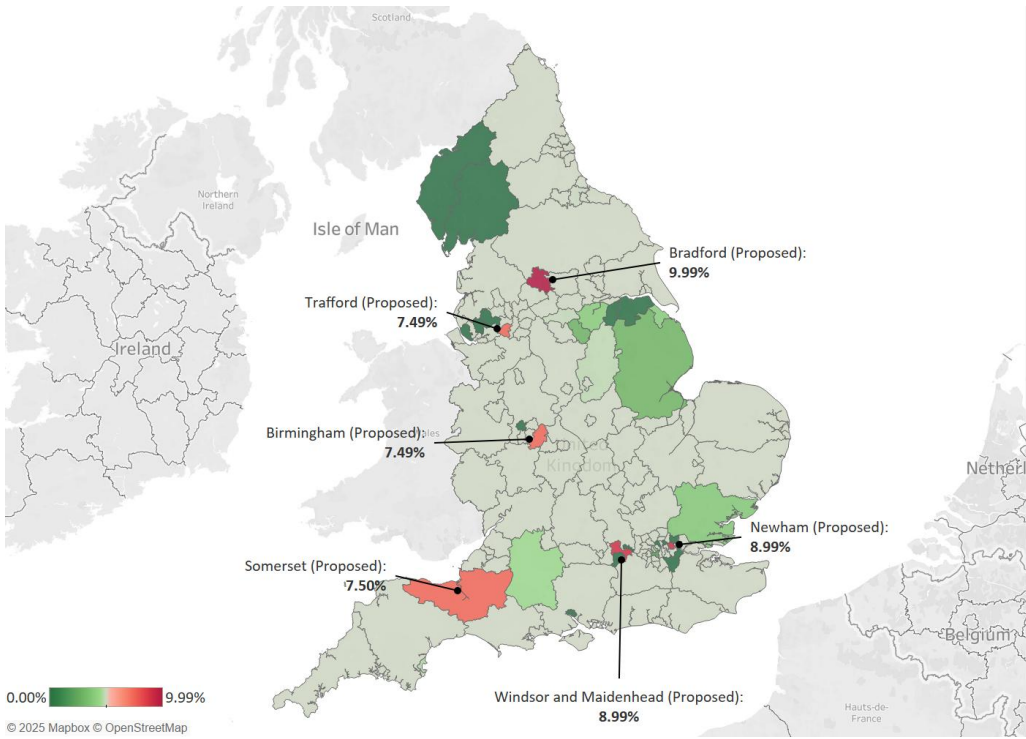
Country	Band	Property Valuation Range	Current Valuation Date	Prior Valuation Range (Wales Only, based on 1991)	Ratio
England	A	$£0 \leq x \leq £40K$	1991-04-01		2 : 3
	B	$£40 < x \leq £52K$			7 : 9
	C	$£52 < x \leq £68K$			8 : 9
	D	$£68 < x \leq £88K$			1 : 1
	E	$£88 < x \leq £120K$			11 : 9
	F	$£120 < x \leq £160K$			13 : 9
	G	$£160 < x \leq £320K$			5 : 3
	H	$£320 > x$			2 : 1
Scotland	A	$£0 \leq x \leq £27K$	1991-04-01		2 : 3
	B	$£27 < x \leq £35K$			7 : 9
	C	$£35 < x \leq £45K$			8 : 9
	D	$£45 < x \leq £58K$			1 : 1
	E	$£58 < x \leq £80K$			131 : 100
	F	$£80 < x \leq £106K$			163 : 100
	G	$£106 < x \leq £212K$			49 : 25
	H	$£212 > x$			49 : 20
Wales	A	$£0 \leq x \leq £44K$	2003-04-01	$£0 \leq x \leq £30K$	2 : 3
	B	$£44 < x \leq £65K$		$£30 < x \leq £39K$	7 : 9
	C	$£65 < x \leq £91K$		$£39 < x \leq £51K$	8 : 9
	D	$£91 < x \leq £123K$		$£51 < x \leq £66K$	1 : 1
	E	$£123 < x \leq £162K$		$£66 < x \leq £90K$	11 : 9
	F	$£162 < x \leq £223K$		$£90 < x \leq £120K$	13 : 9
	G	$£223 < x \leq £324K$		$£120 < x \leq £240K$	5 : 3
	H	$£324 < x \leq £424K$		$£240 > x$	2 : 1
	I	$£424 > x$			3 : 1

Figure 3.7: Annual Band D Council Tax Changes, 2010–2023



Source: Department for Levelling Up, Housing & Communities, 2024

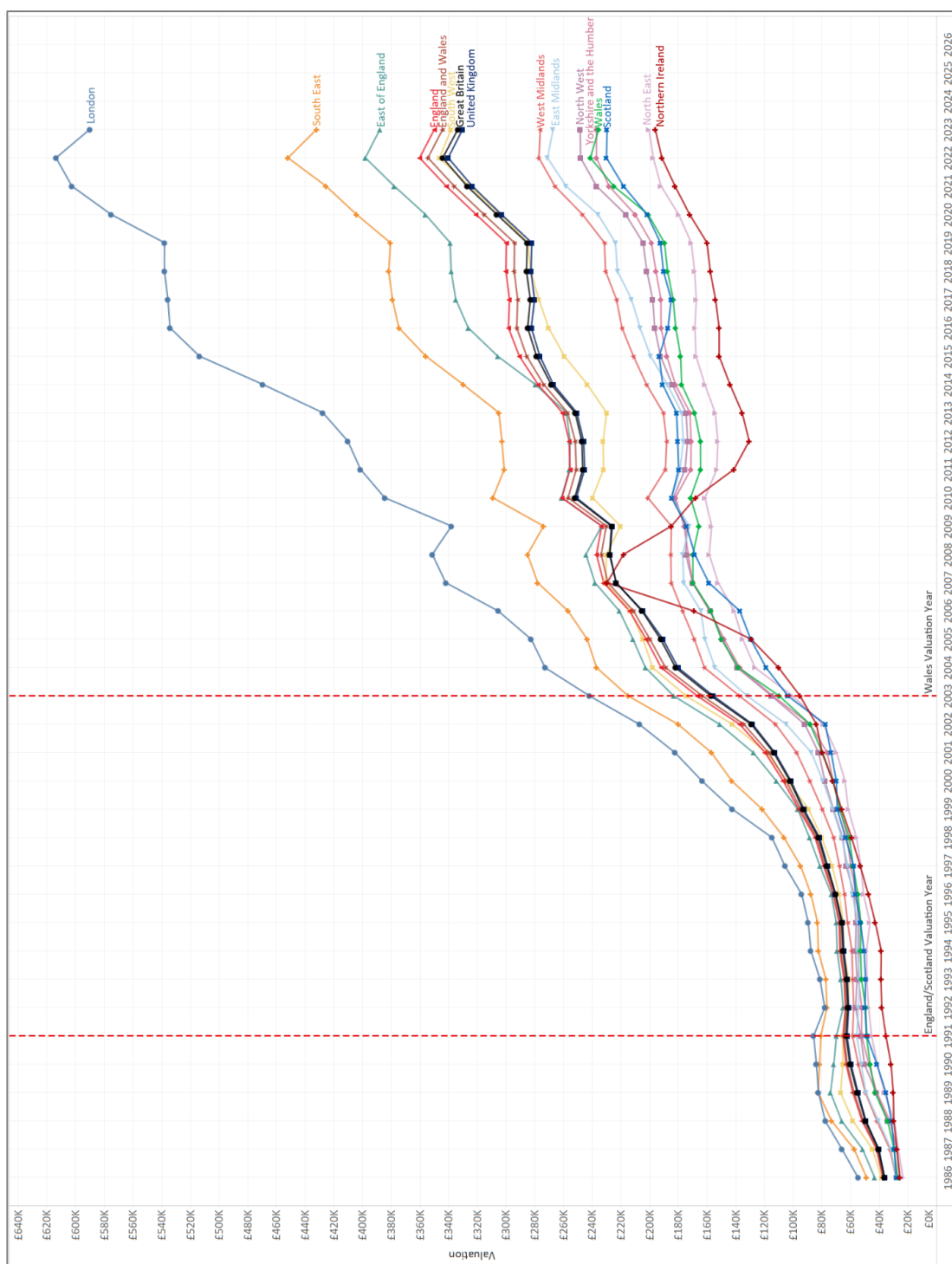
Map 1: Proposed and Confirmed Council Tax Increases for 2024-25 for England



Source: Wells, 2025

Note: Choropleth map showing proposed council tax increases by local authority district. Areas exceeding the referendum threshold are highlighted, while most districts cluster near the standard maximum.

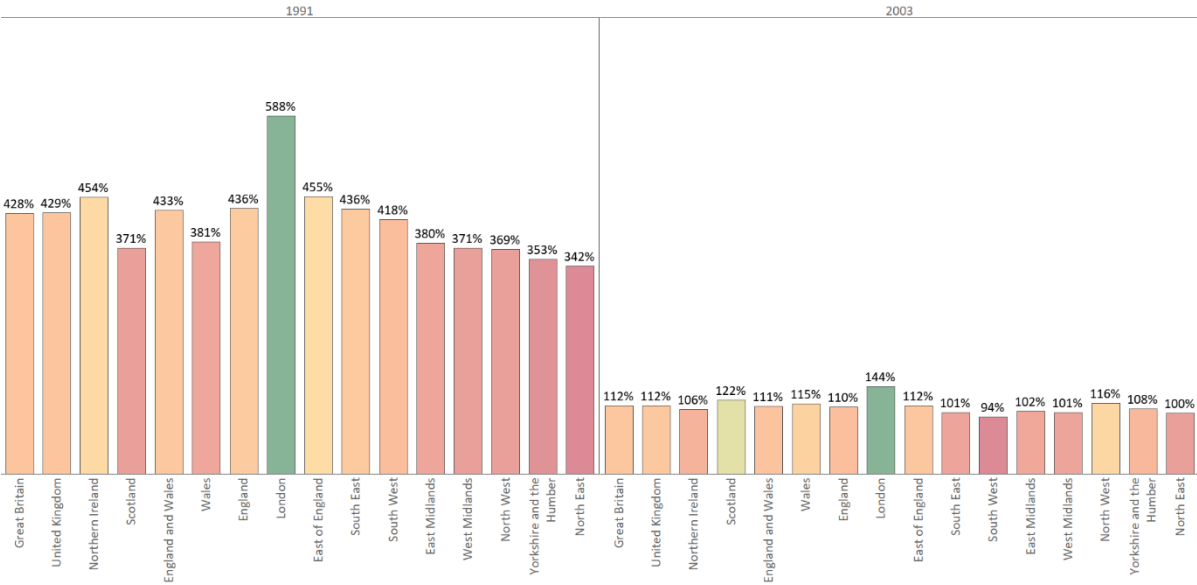
Figure 3.8: Annual Avg Prices by Region from 1986-2023



Source: ONS, 2024

Note: Lines show annual mean prices by region with vertical reference lines marking revaluation years.

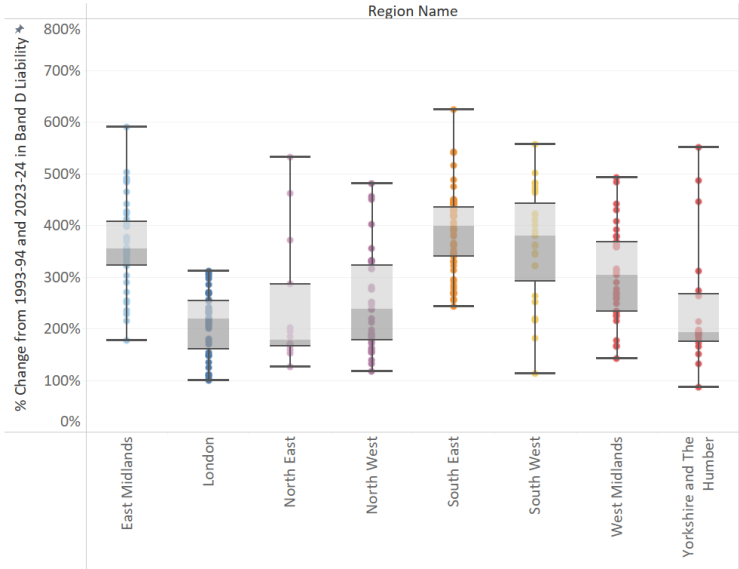
Figure 3.9: Price Growth by Region since 1991 and 2003



Source: ONS, 2024

Note: Bars display percentage change in average property prices by region between 1991 and 2023.

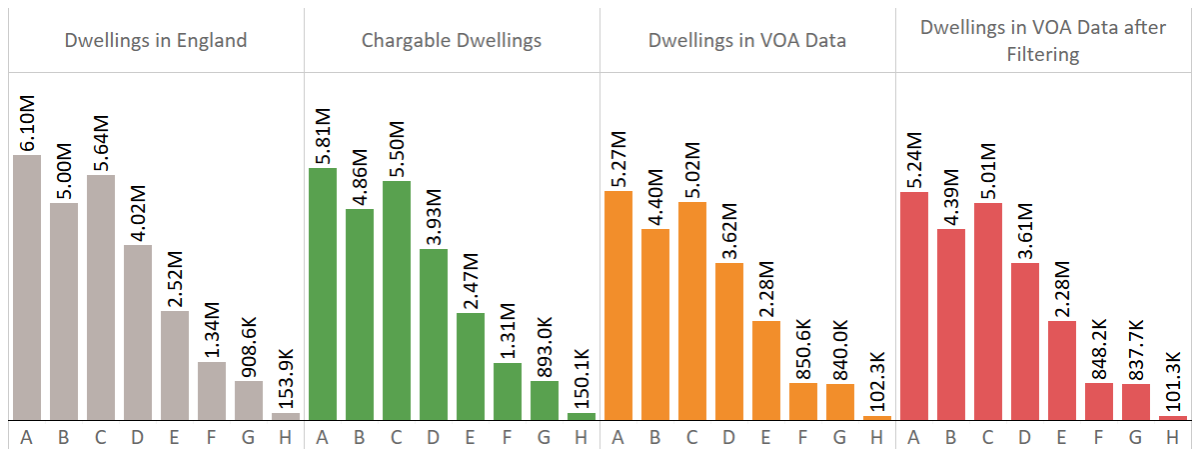
Figure 3.10: Distribution of Local Authorities' % Change in Band D Liability (Pre-CTS) between 1993-94 and 2023-24 by Region



Source: UK.gov, 2024

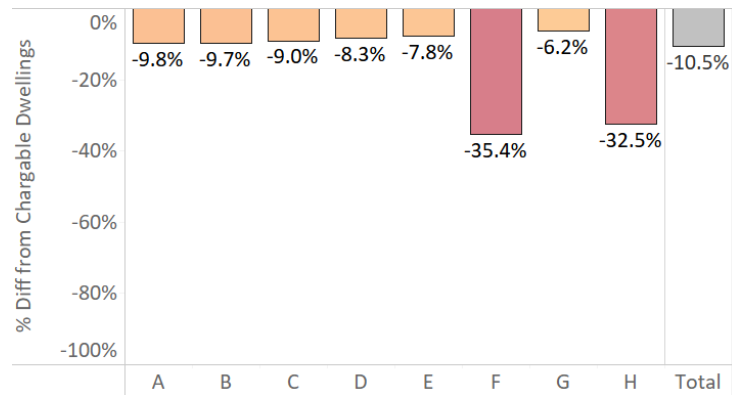
Note: Box-and-whisker plots show LAD-level percentage changes in average liability, grouped by region.

Figure 3.11: Dwelling Counts in England from Various VOA Sources and the Filtered Counts



Note: Bars compare total dwellings in England across VOA official counts, chargeable counts, raw data, and filtered data.

Figure 3.12: Shrinkage in Final Dwelling Counts per Band from Official VOA Chargeable Dwellings for 2023-24



Note: Bars show the share of properties missing between official VOA chargeable counts and modeled counts, highlighting data loss by band. The majority of the difference is due to fewer records present in the per dwellings VOA rather than filtering.

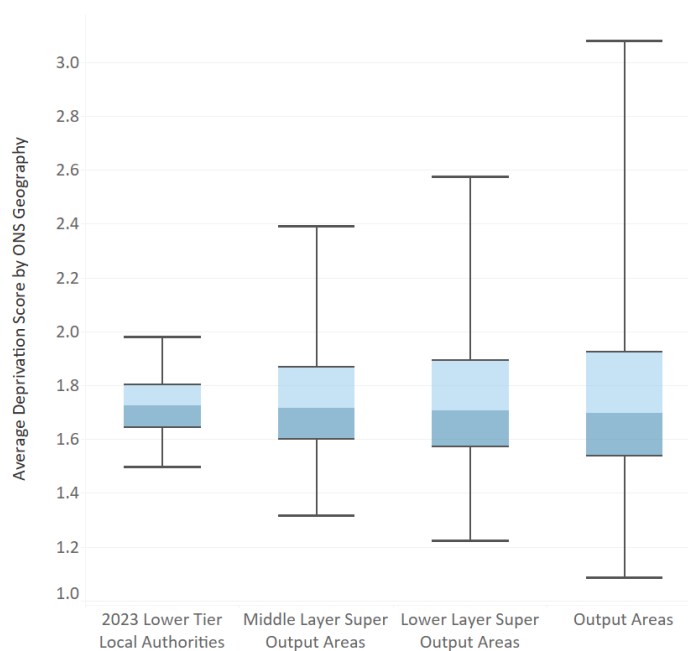
Table 3.15: Summary of Select Responses to Wales' A Fairer Council Tax Consultation

#	Question Title	Question Abridged	Response			
			Positive (Yes)	Negative (No)	Neither Positive or Negative	No Response
1	2025 Revaluation	Should there be a council tax revaluation in 2025 based on 2023 property values?	439 (43%)	562 (55%)		23 (2%)
2	Add and refit bands	Should more council tax bands be added and existing bands be refitted?	498 (49%)	489 (48%)		37 (4%)
5	Rolling Revaluations	Should council tax be revalued at least every five years?	378 (37%)	612 (60%)		34 (3%)
6	Property Improvements	Should properties be rebanded immediately after significant improvements?	368 (36%)	602 (59%)		54 (5%)
10	Flexibility of Single Adult and Empty ..	Should the Welsh Government have more flexibility over single adult and empty property discounts?	208 (20%)	169 (17%)	229 (22%)	418 (41%)
13	CTRS Design	Should council tax reduction continue to be means-tested? Any suggestions for improvement?	347 (34%)	550 (54%)		127 (12%)

#	Question Title	Question Abridged	Number of Written Responses	Response	
3	Transitional Arrangements	What factors should be considered in designing transitional arrangements?	610	Consideration should be made for fixed income households.	79 (13.0%)
				Expressed concerns regarding the cost-of-living crisis and ability to pay adjusted rates.	268 (43.9%)
				Recommended staggering adjustments.	128 (21.0%)
7	Appeals and Debt Management	What are your views on taxpayer appeal rights and council tax debt management?	514	Banding appeals should be removed.	21 (4.1%)
				Calls for various debt management approaches.	93 (18.1%)
				Simplify appeals process.	87 (16.9%)
				The current appeals process should be maintained.	87 (16.9%)
8	Modernisation and Transparency of Service	How can the council tax system be modernized and made more transparent?	419	Better information and education about Council Tax.	38 (9.1%)
				Call for national Council Tax information service.	17 (4.1%)
				Increased transparency.	122 (29.1%)
				Modernize the Council Tax system.	84 (20.0%)
11	Disabled Adapted Properties	How can council tax reductions for disabled-adapted properties be improved?	334	Abolish disabled adapted properties reduction	62 (18.6%)
				Increase disabled adapted properties reduction	63 (18.9%)
				Retain current disabled adapted properties reduction	40 (12.0%)

Source: Welsh Government, 2022

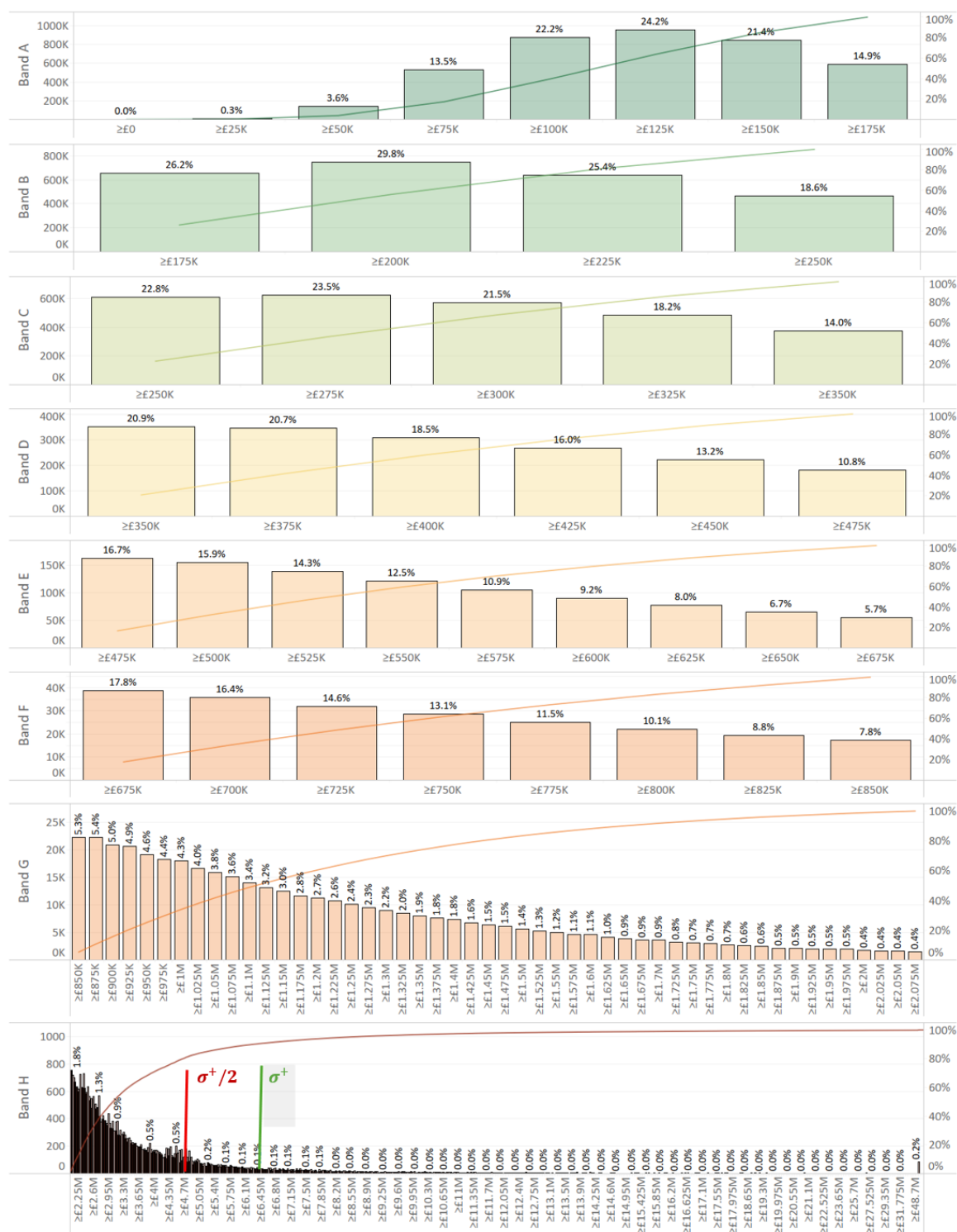
Figure 3.13: Distribution of Deprivation Scores within Various Geography Levels



Source: ONS, 2024

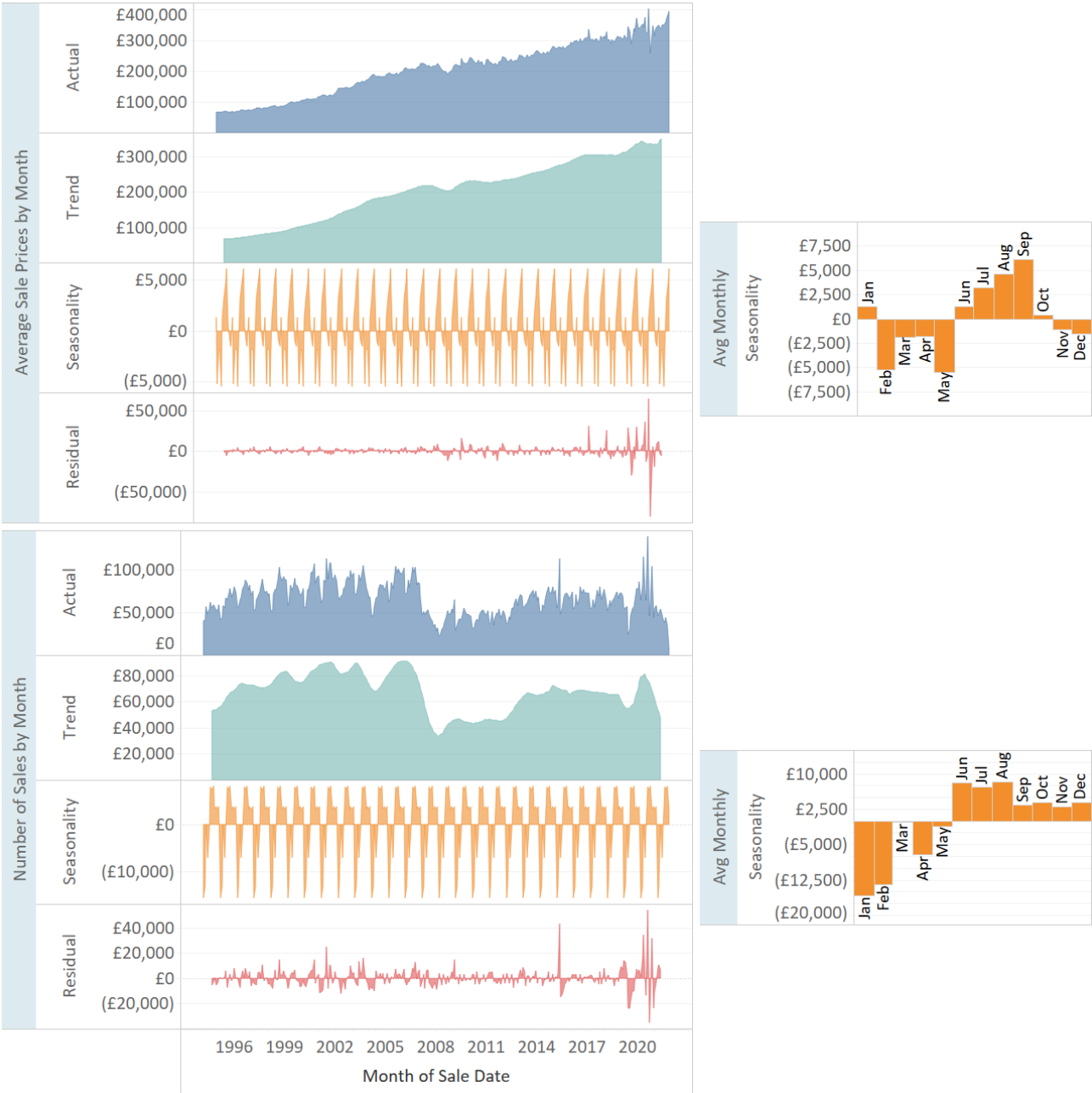
Note: Box-and-whisker plots show how deprivation varies across LAD, MSOA, LSOA, and OA levels.
Higher scores indicate more deprived areas.

Figure 3.14: Distribution of Dwellings based on Contemporary Estimated Price (in £25K Bands)



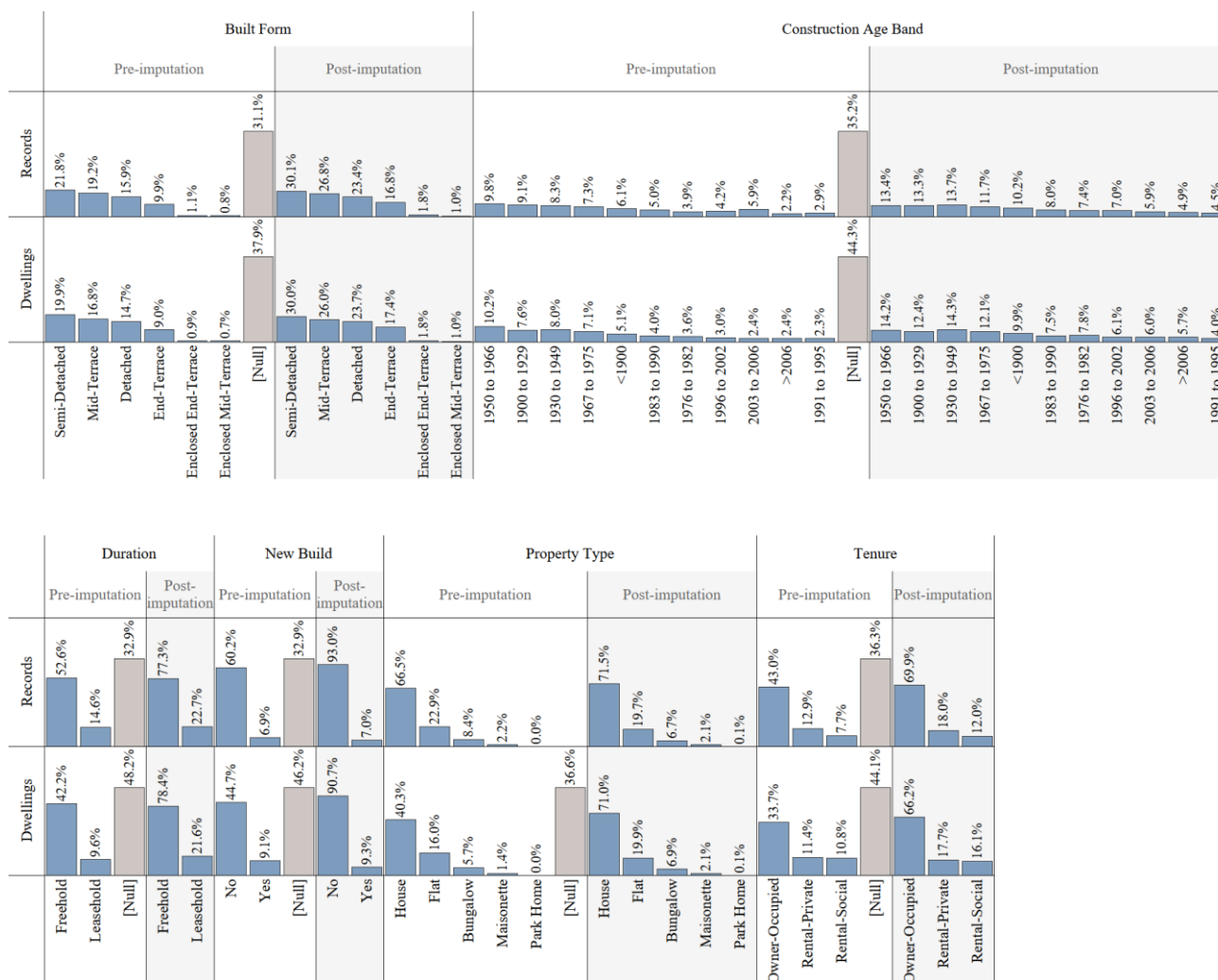
Note: Histogram shows property counts in £25K value bins. Skewness across bands illustrates uneven value distributions, especially in lower and upper bands.

Figure 3.15: Decomposed Average Month Sale Prices and Transaction Counts, 1995 - 2022



Note: Line plots show overall trend, seasonality, and residuals of average sale prices from 1995 to 2022.

Figure 3.16: Categorical Distribution of Values Pre-Imputation and Post-Imputation



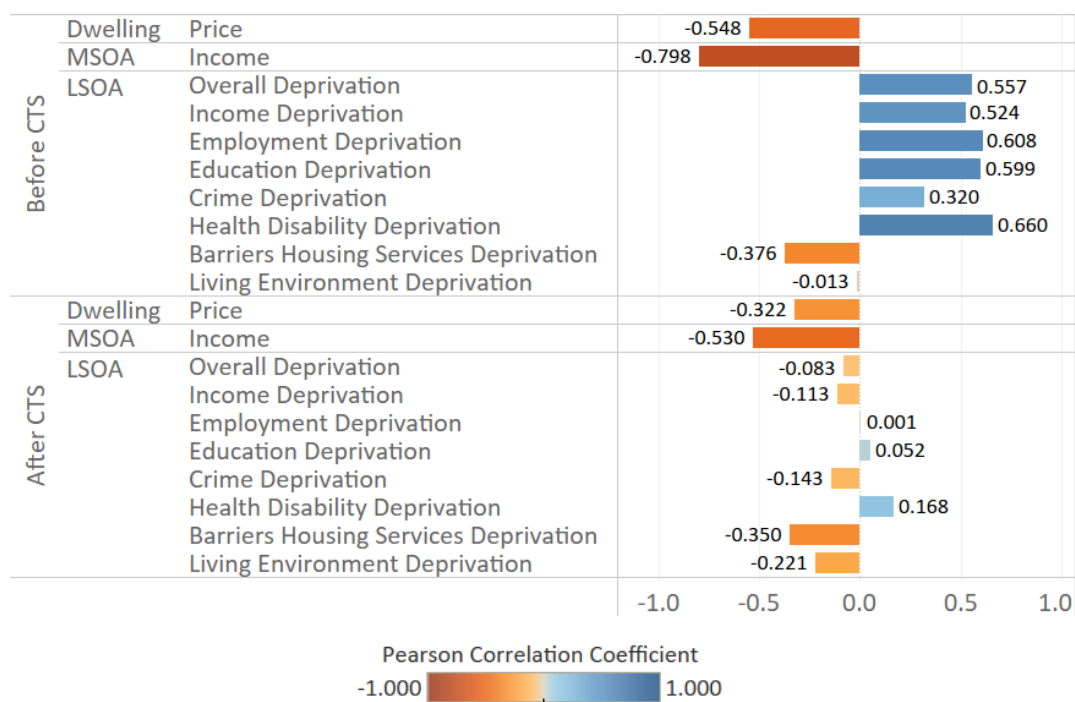
Note: Displays the percentage of records and dwellings associated with each categorical value, illustrating missingness before imputation.

Table 3.16: Summary Statistics of the Numeric Variables Pre-Imputation and Post-Imputation

	Current Energy Efficiency		Number of Inhabitable Rooms		Total Floor Area	
	Pre-imputation	Post-imputation	Pre-imputation	Post-imputation	Pre-imputation	Post-imputation
Min	1.00	1.00	0.00	0.00	0.01	4.94
1st Quartile	58.00	60.00	3.00	4.00	62.00	68.00
Mean	65.36	64.32	4.34	4.47	88.93	91.02
Median	67.00	64.00	4.00	4.00	79.00	84.52
3rd Quartile	74.00	70.00	5.00	5.00	101.00	102.95
Max	991.00	991.00	137.00	782.00	47,016.00	47,016.00
Std Dev	13.15	10.71	1.77	1.58	53.98	46.41

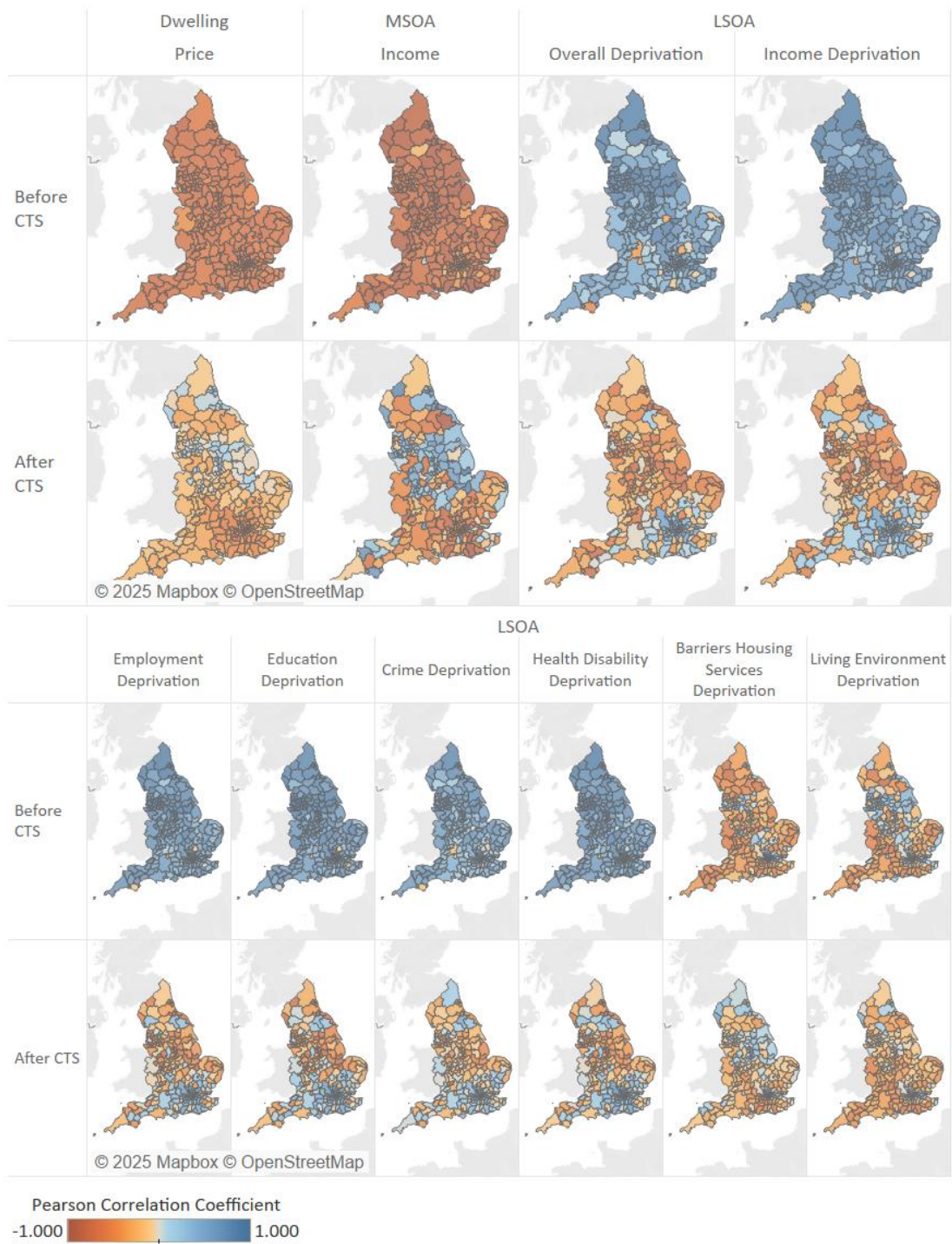
	Adjusted Price		LSOA Deprivation Score		MSOA Encode
	Pre-imputation	Post-imputation	Pre-imputation	Post-imputation	Post-imputation
Min	8,587.94	8,587.94	0.54	0.54	53,770.25
1st Quartile	199,858.78	199,858.78	9.71	9.71	178,951.44
Mean	371,554.20	371,554.20	20.73	20.73	280,449.42
Median	293,361.97	293,361.97	16.92	16.92	247,174.66
3rd Quartile	434,002.89	434,002.89	27.88	27.88	337,560.24
Max	399,677,606.05	399,677,606.05	92.74	92.74	3,009,194.31
Std Dev	521,313.05	521,313.05	14.62	14.62	160,572.97

Figure 3.17: England-wide Pearson Correlation Coefficient



Note: Bars show Pearson correlation coefficients between effective tax rates (pre- and post-CTS) and variables such as property value, income, and deprivation.

Map 2: Correlation of Tax Rate vs. Estimated Price, MSOA Income and LSOA Deprivation



Note: Maps show LAD-level correlations between effective tax rates (pre- and post-CTS) and three variables: estimated property values, MSOA-level income, and LSOA-level deprivation (overall and income-specific). Smaller inset maps display additional deprivation dimensions.

Table 3.17: Win, Neutral, and Loss Classification by Band Change per Simple Revaluation Counterfactual

		Band Change Classification		
		Win	Neutral	Loss
1.1A	Simple Revaluation (National Constraints)	26.9% 12.0M	48.7% 21.7M	24.4% 10.9M
1.1B	Simple Revaluation (LAD Constraints)	23.5% 10.5M	54.9% 24.5M	21.5% 9.6M
1.1C	Simple Revaluation (CoLAD Constraints)	26.9% 12.0M	48.7% 21.7M	24.4% 10.9M

Note: Each cell presents the percentage and number of dwellings that fall into the categories of winners (lowering of band), losers (increase in band), or neutral (remain in the same band). The rows refer to the primary simple revaluation model (1.1A), which is nationally constrained both in terms of dwelling counts per band (to match current distributions) and revenue constraints. The other counterfactuals apply LAD constraints for both revenue and dwellings (1.1B) or for revenue only (1.1C). These scenarios are mentioned only in a footnote in the paper but indicate potential inefficiencies that may offset some benefits when utilizing localised models.

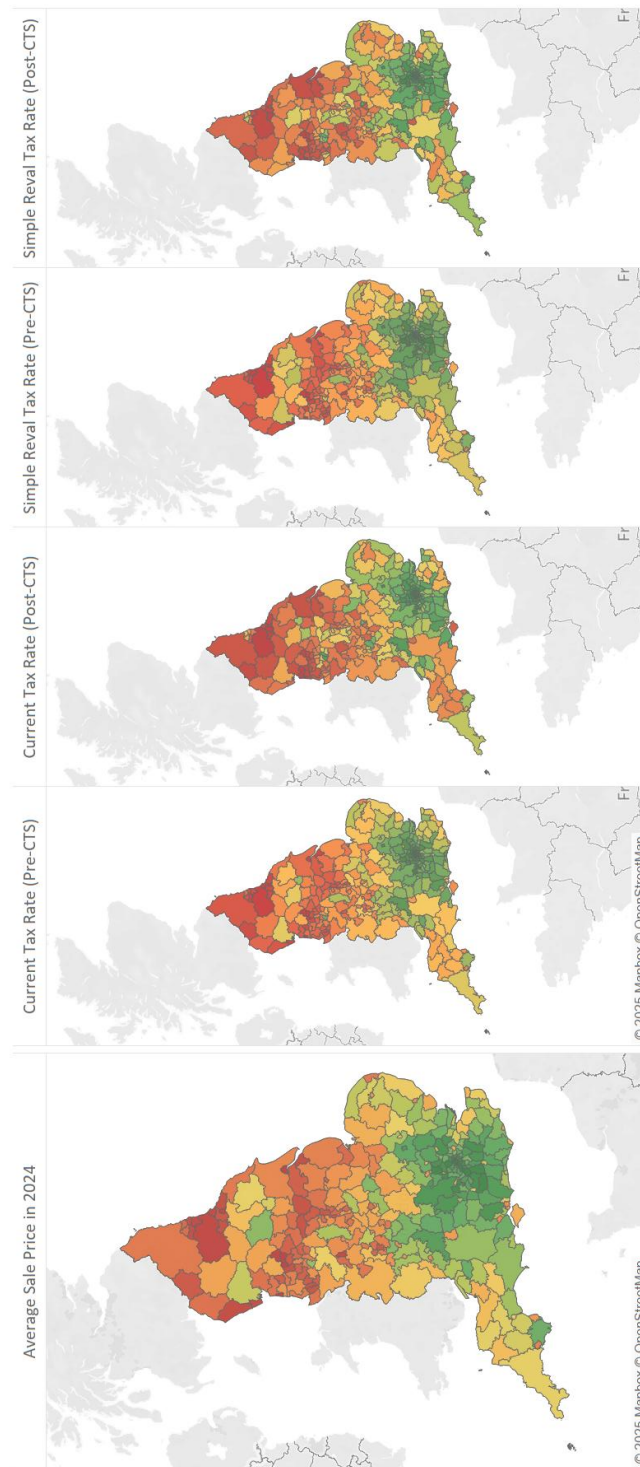
Table 3.18: Win, Neutral, and Loss Classification by Tax Liability (plus Avg Change in Liabilities) per Counterfactual

			Compared to CURRENT	
			Loss	Win
Revaluation Only	1.1A	Simple Revaluation (National Constraints)	9.5M 42.69% £185	12.8M 57.31% (£249)
			Compared to SIMPLE REVALUATION	
			Loss	Win
Rewighted Multipliers	2.1	Scotland's Current 2017 Multiplier Distribution (Revenue Nationally Constrained)	4.1M 18.22% £165	18.2M 81.78% (£38)
	2.2	Scotland's Proposed Multiplier Distribution (Revenue Nationally Constrained)	4.1M 18.22% £342	18.2M 81.78% (£81)
	2.3	New Band Range Mean Weighted Multipliers (Revenue Nationally Constrained)	7.7M 34.38% £559	14.6M 65.62% (£220)
	2.4	Estimated Value Mean Weighted Multipliers (Revenue Nationally Constrained)	7.7M 34.38% £326	14.6M 65.62% (£112)
Band Structure Reforms	3.1	Add Band I (Wales 2005) (Revenue Nationally Constrained)	3.6M 16.29% £17	18.7M 83.71% (£3)
	3.2	Split Bands G and H (Revenue Nationally Constrained)	3.9M 17.27% £29	18.5M 82.73% (£9)
	3.3	Split Band A (Revenue Nationally Constrained)	19.7M 88.25% £35	2.6M 11.75% (£148)
	3.4	Split All Bands (Revenue Nationally Constrained)	19.7M 88.25% £34	2.6M 11.75% (£148)
Band Structure Reforms with Value Reweighted Multipliers	4.1	Full Band Splits with Estimated Value Mean Weighted Multipliers (Revenue Nationally Constrained)	10.0M 44.72% £329	12.3M 55.28% (£238)
Alternative Tax Systems	5.1	Flat Mill Levy	8.4M 37.53% £401	13.9M 62.47% (£200)
	5.2	Flat Mill Levy with Income Deprivation CTS	9.4M 42.22% £472	12.9M 57.78% (£352)
	5.3	Continuous Progressive Rate (1% Cap) with Current CTS	0.4M 1.64% £1,715	21.9M 98.36% (£1,140)
	5.4	Continuous Progressive Rate (1% Cap) with Income Deprivation CTS	4.7M 20.91% £1,848	17.6M 79.09% (£713)

Difference in Annual Liabilities
 (£500)  £500

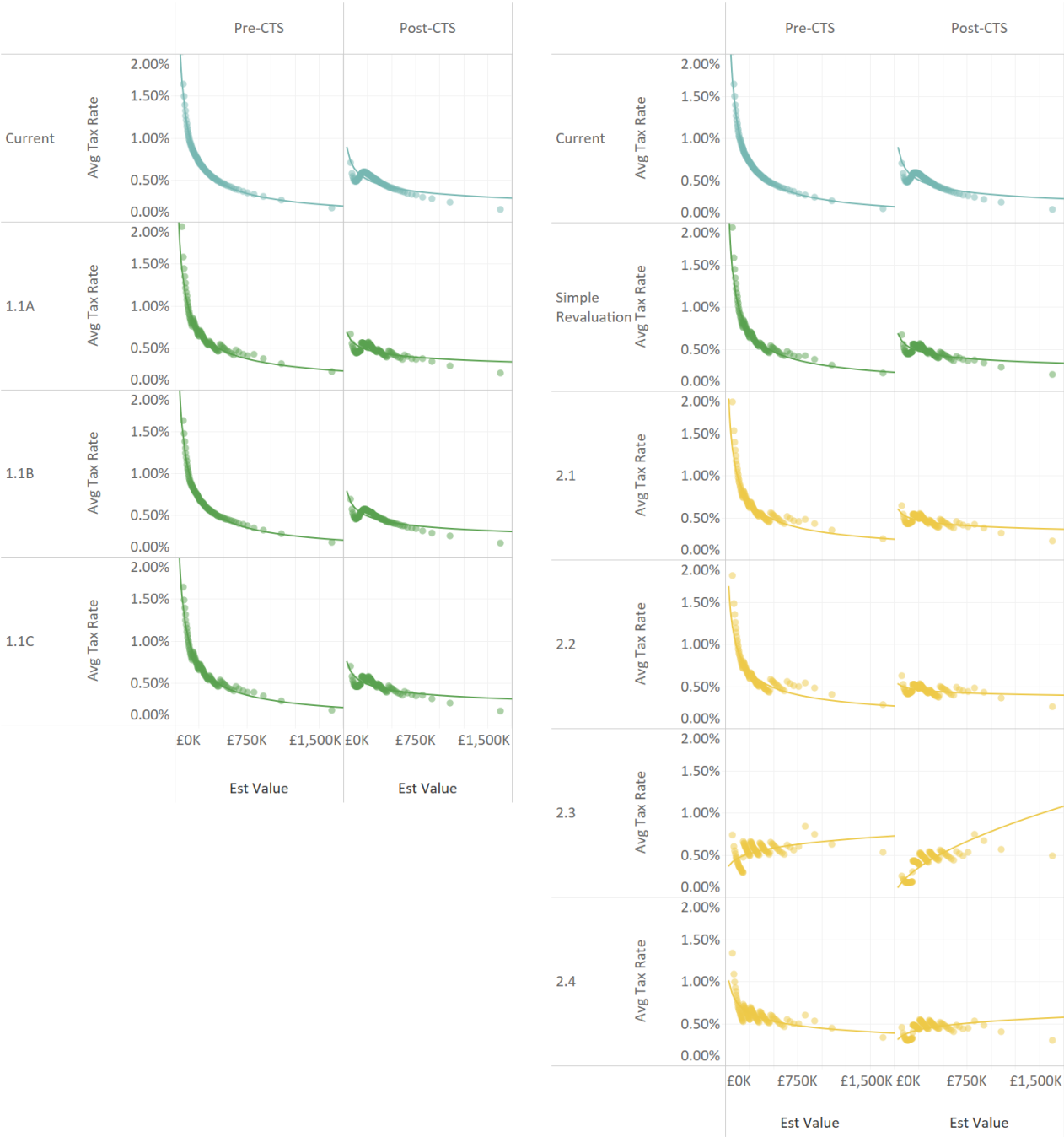
Note: Each cell reports three values: number of dwellings, percentage of dwellings, and average change in annual liability. Rows correspond to counterfactual scenarios; comparisons are made against the simple revaluation baseline (1.1A). Average liability differences vary substantially across counterfactuals, reflecting differences in model structure.

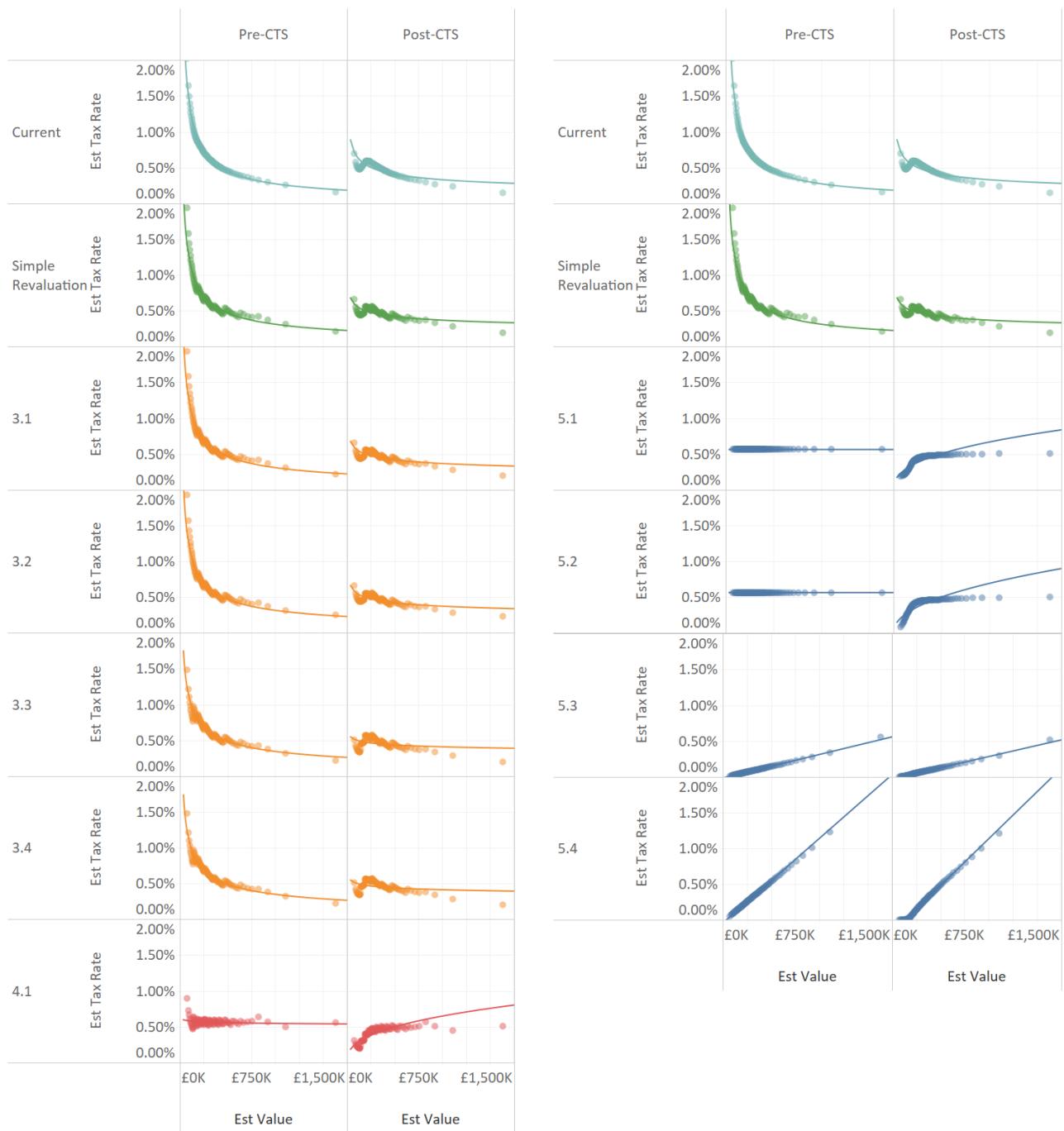
Map 3: Average 2024 Price and Tax Rates by LAD



Note: Choropleth maps compare current average tax rates and 2024 property prices by LAD to those under a simple revaluation scenario, illustrating shifts in spatial patterns.

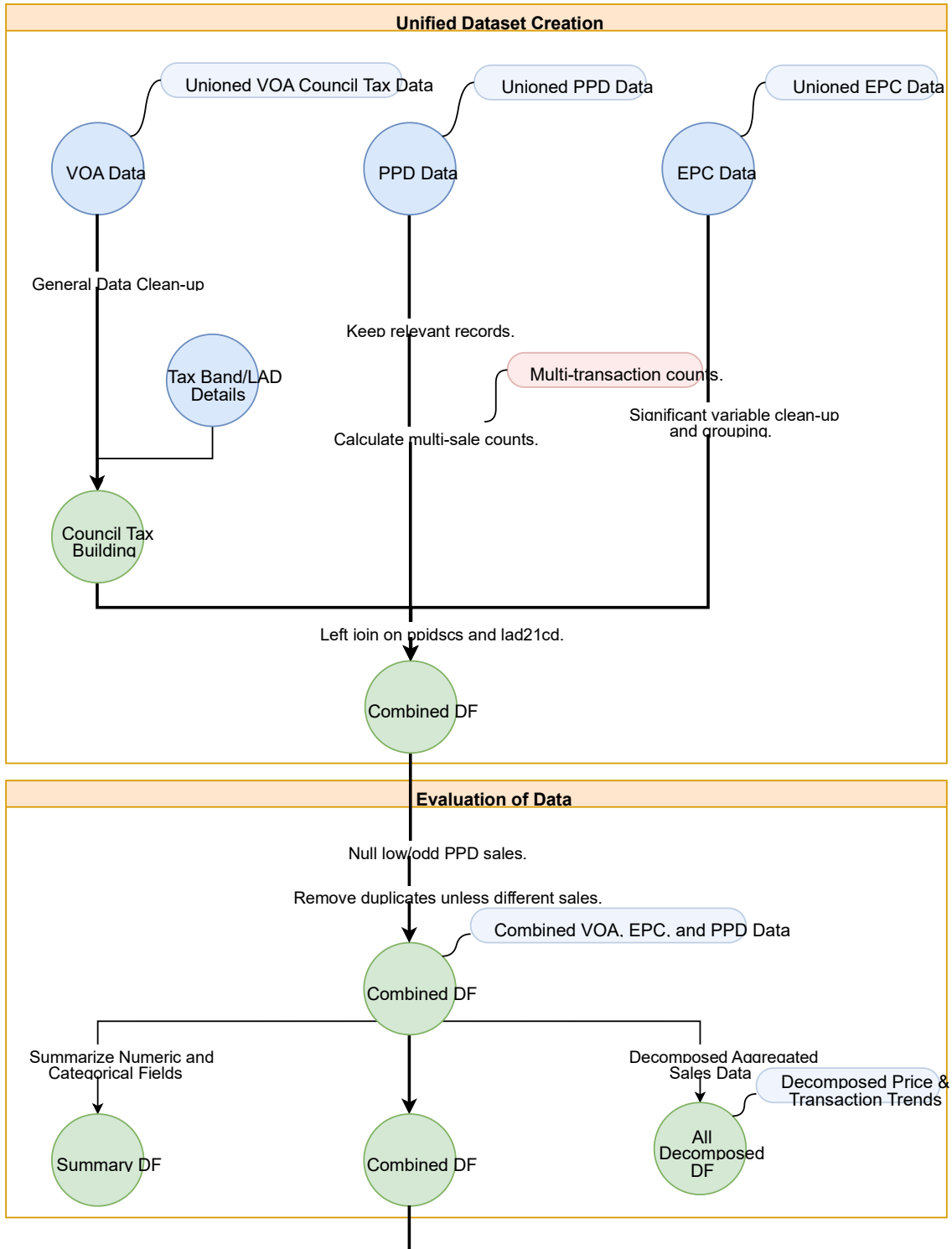
Figure 3.18: Power Line of Best Fit through Binned Tax Rate and Property Value by Benchmark and Counterfactual

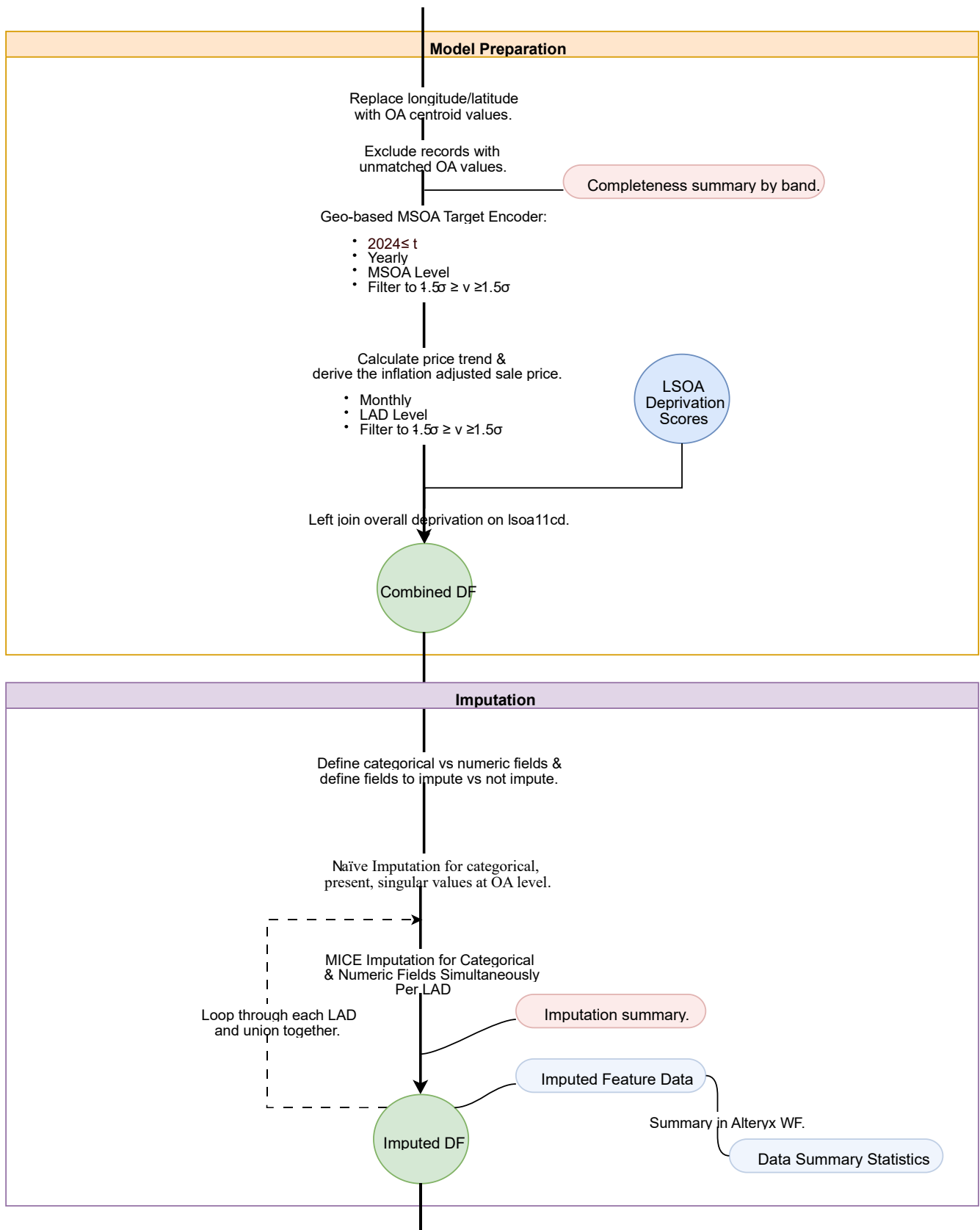


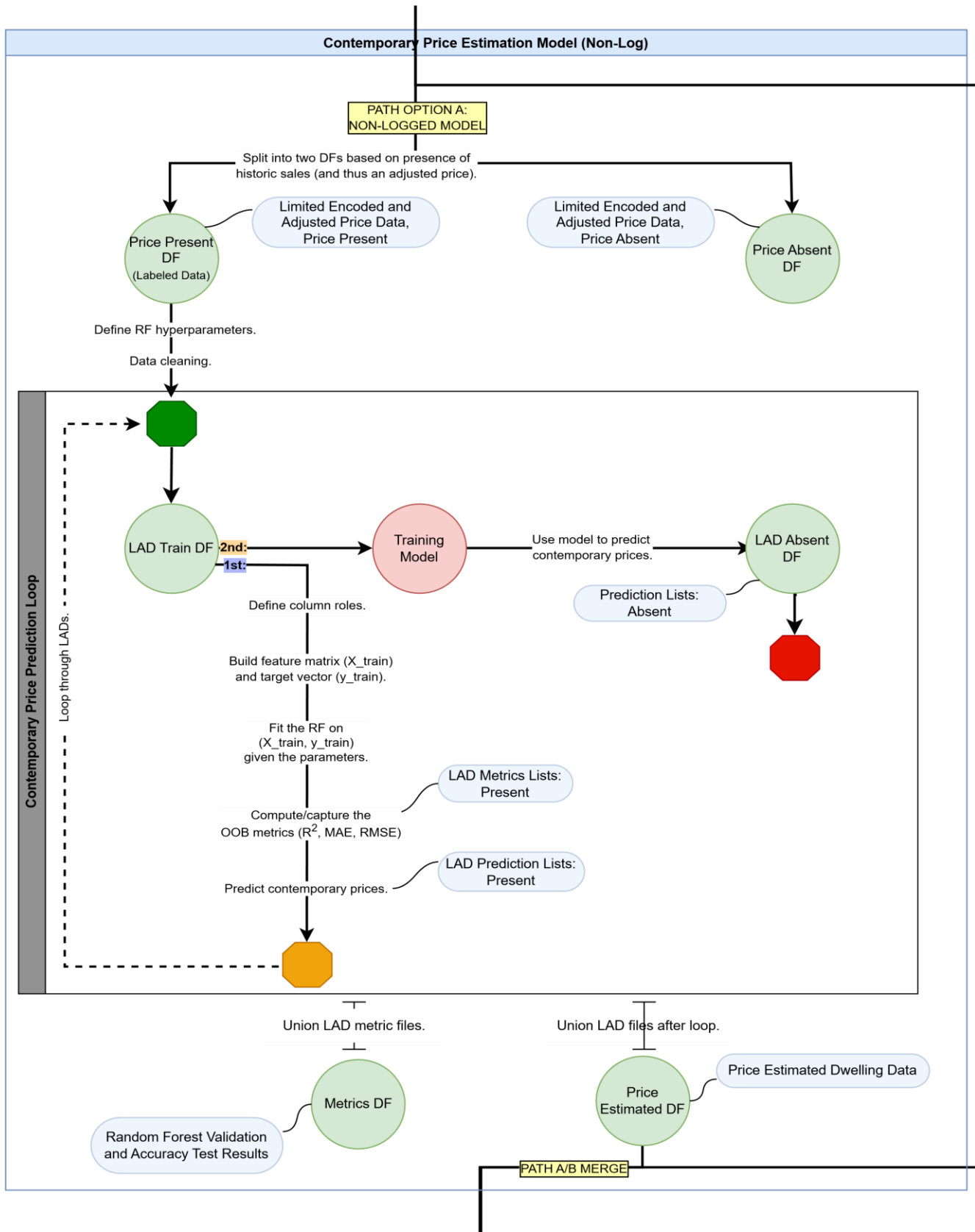


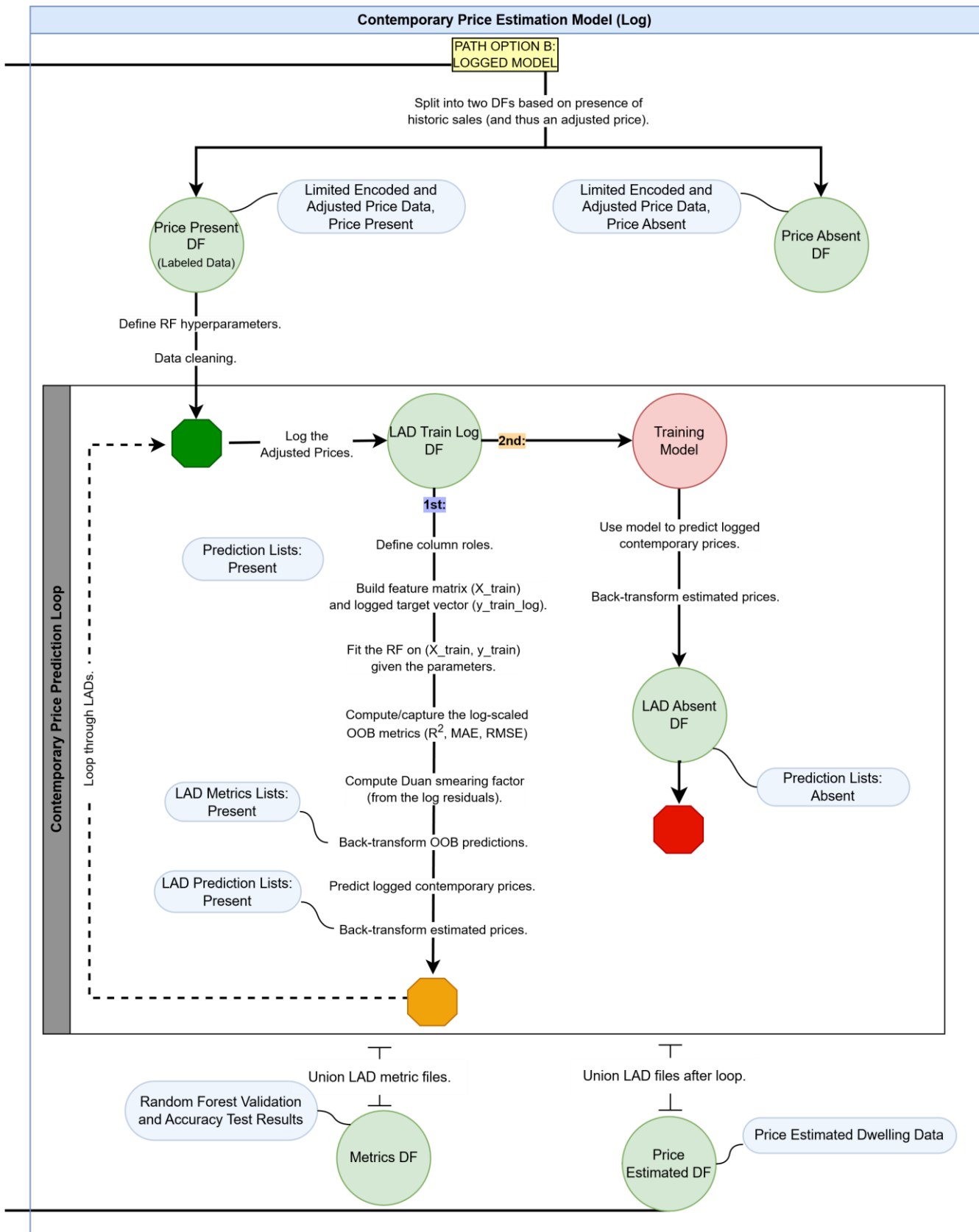
Note: Scatterplots with 100 binned values and fitted power curves show how the relationship between value and tax rate changes under different counterfactuals.

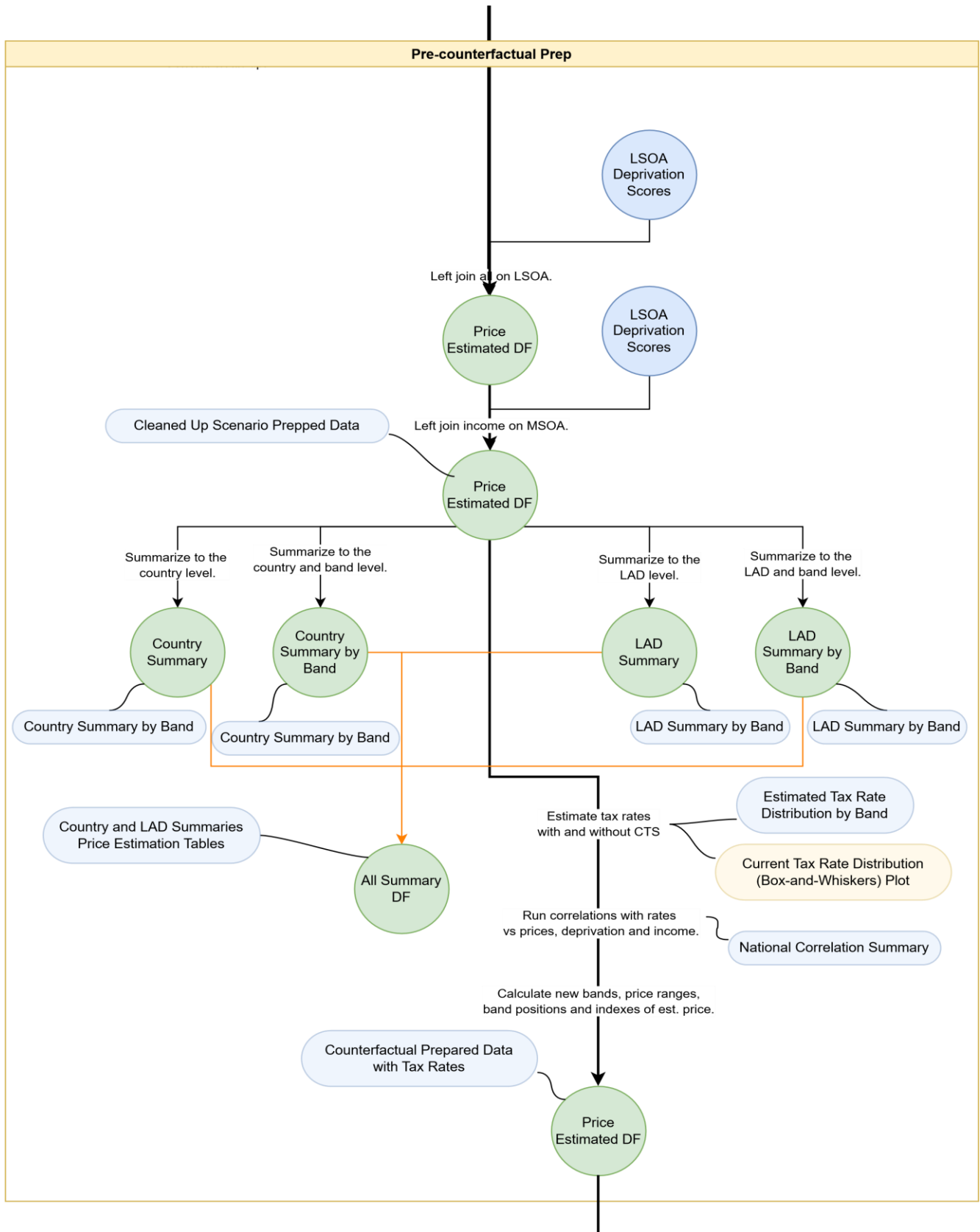
Appendix C: Code Process Flow Map

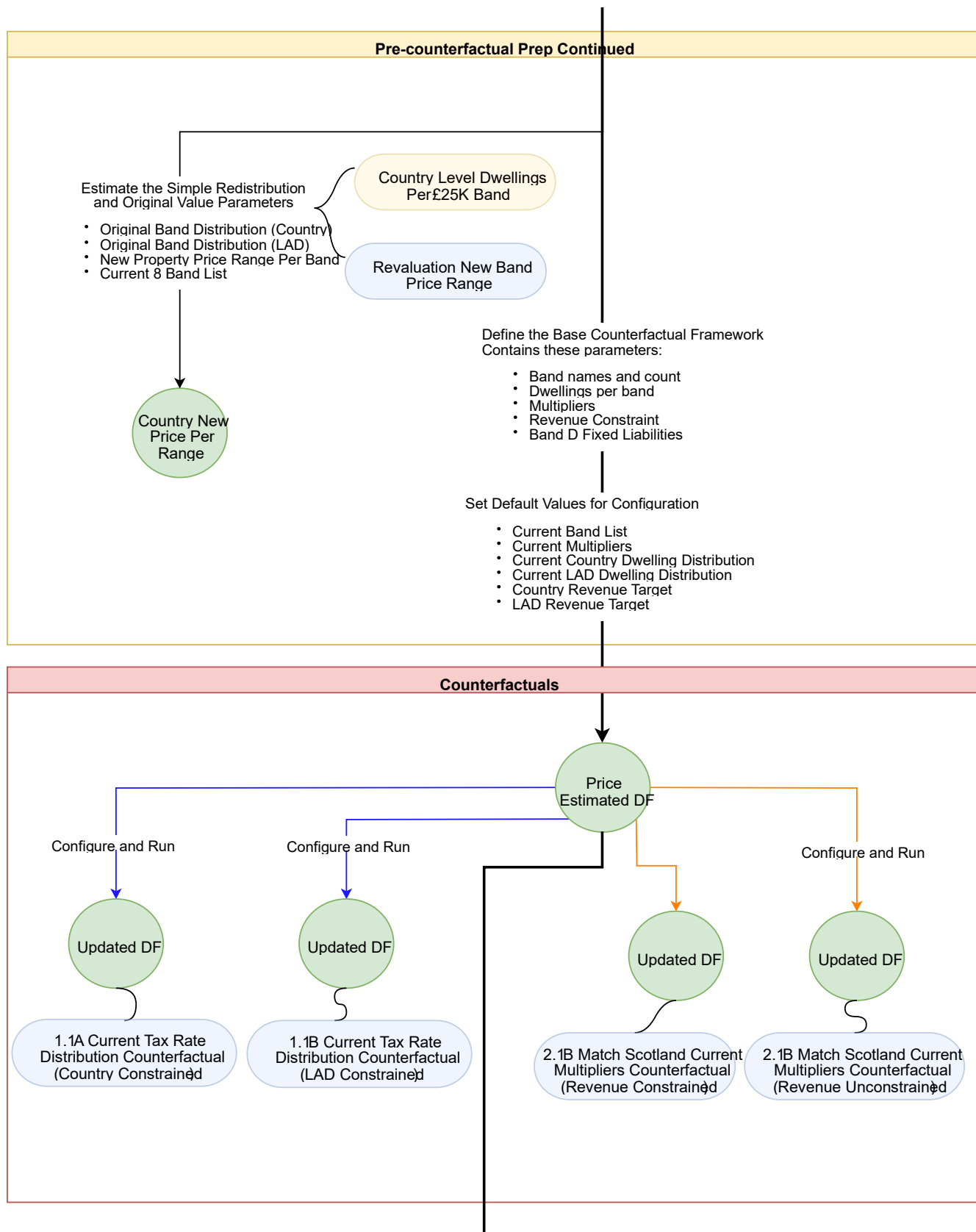




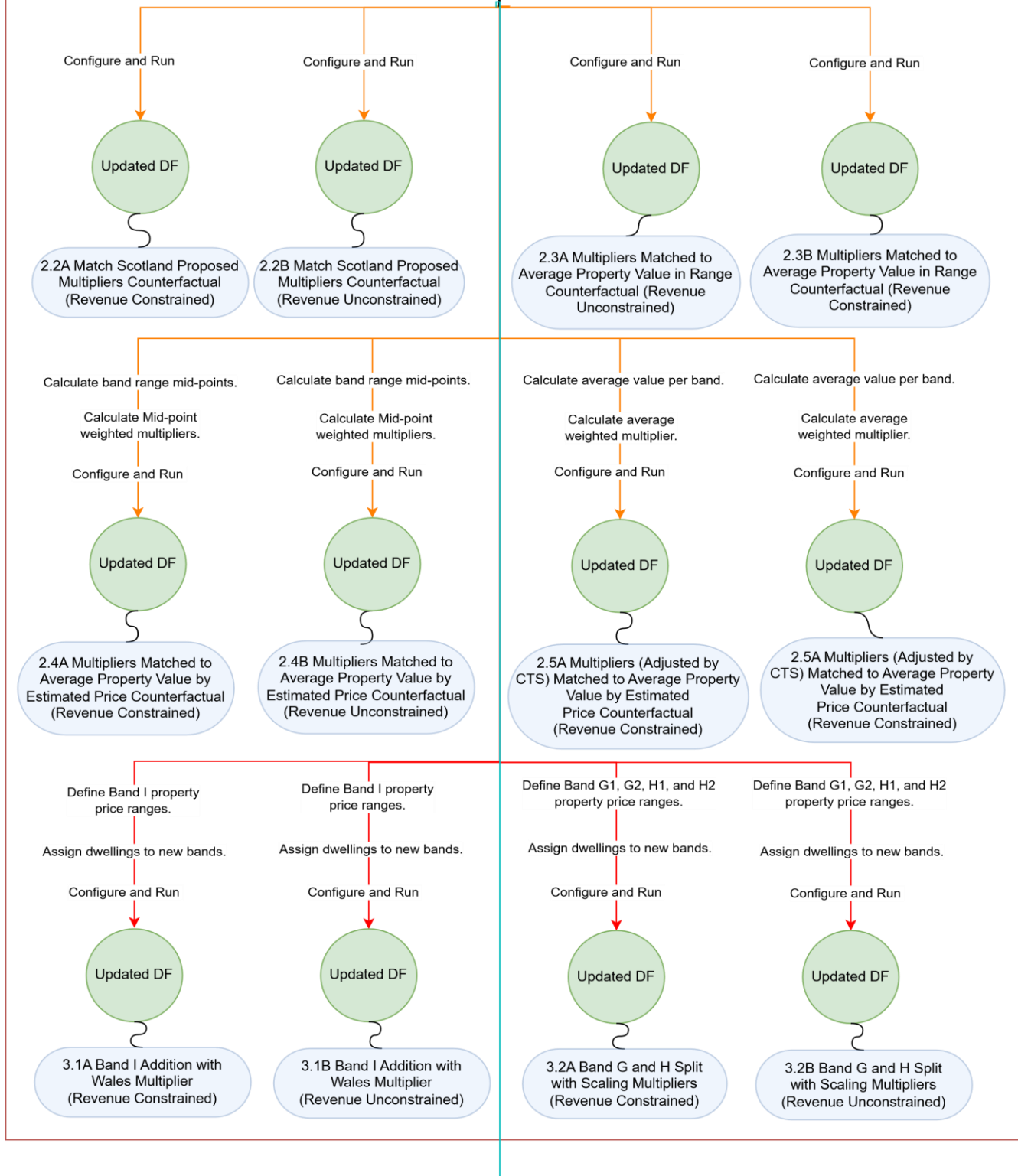




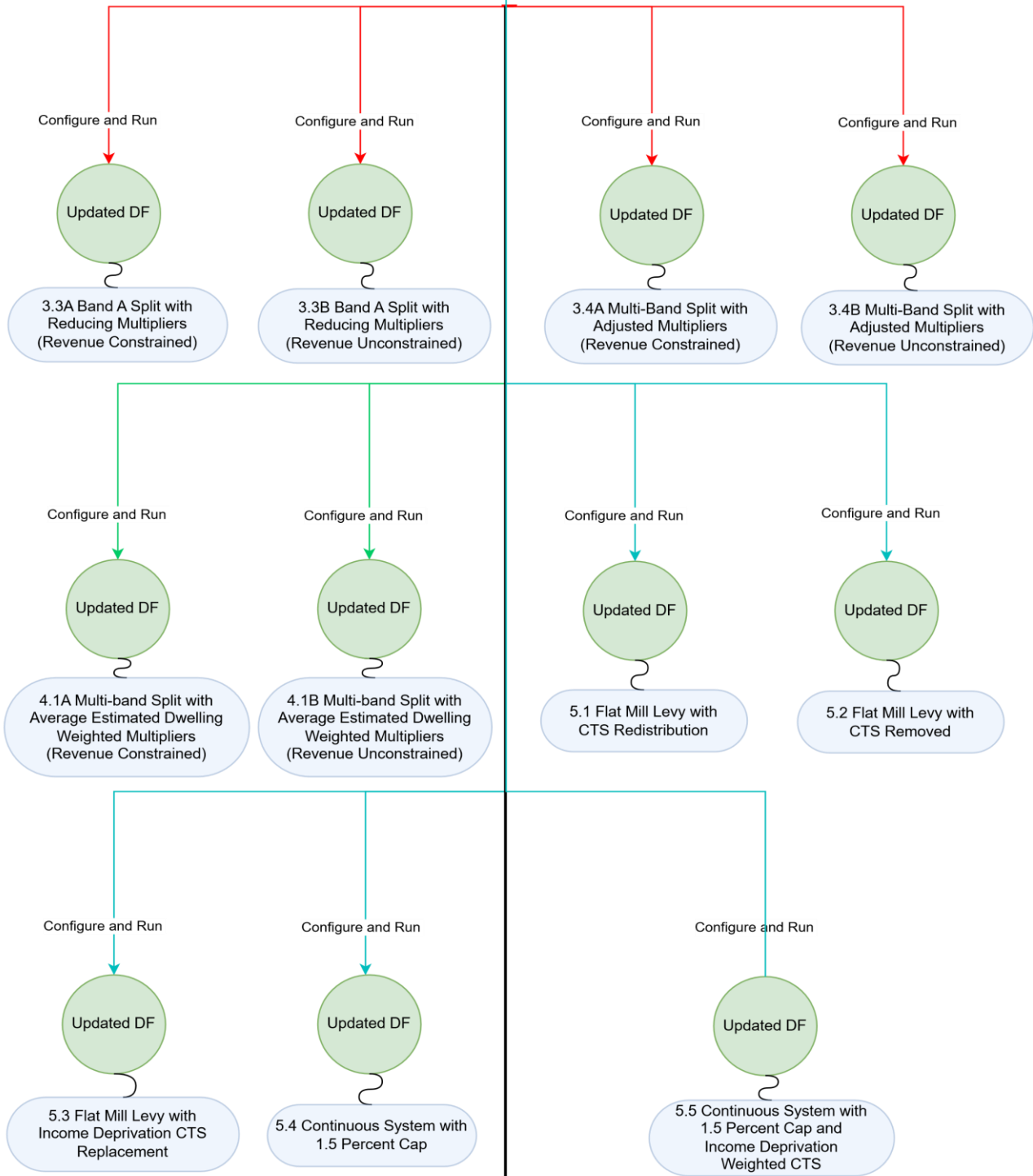


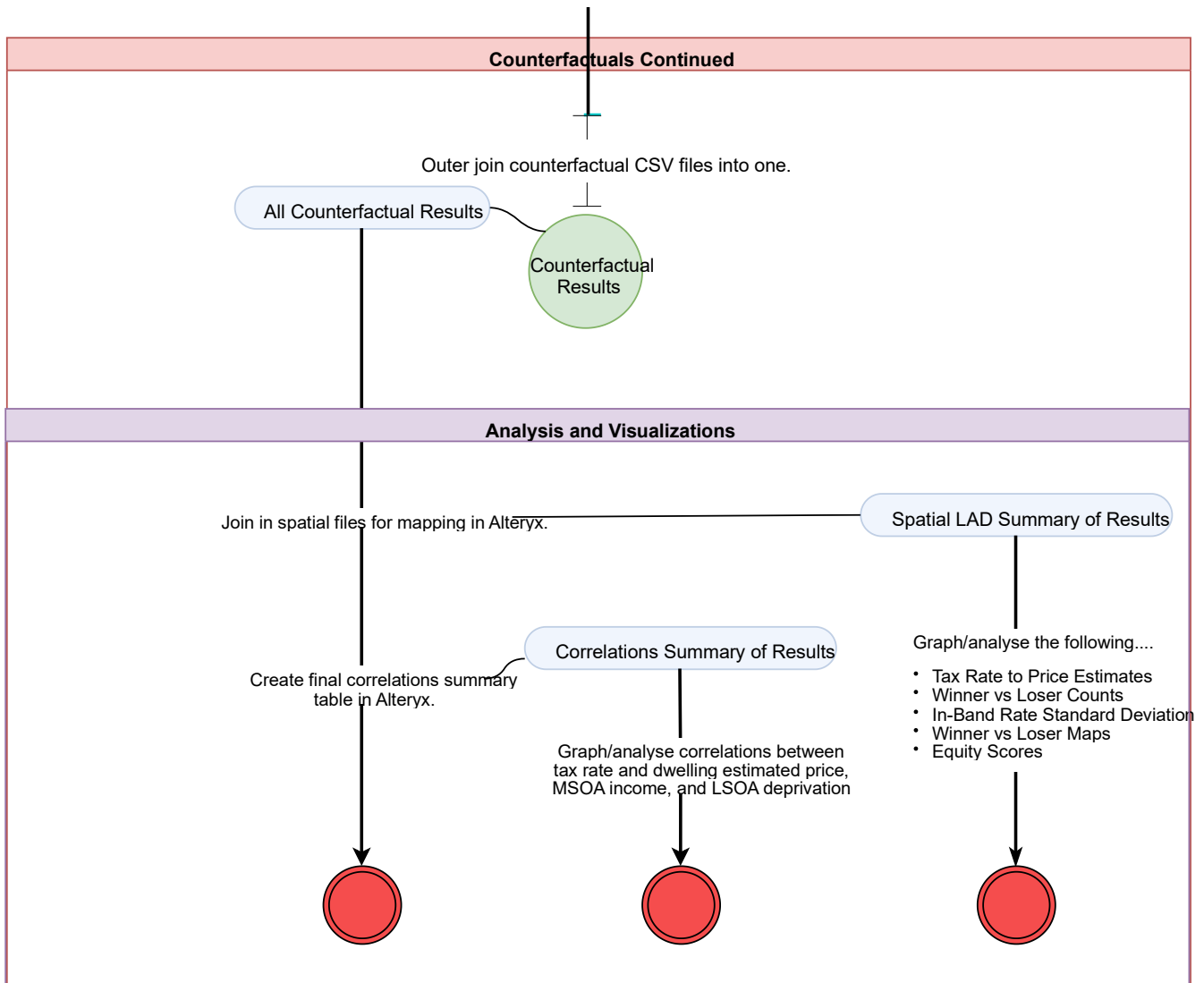


Counterfactuals Continued



Counterfactuals Continued





Conclusion

Across these three papers, this dissertation demonstrates the versatility and value of modern counterfactual analysis in advancing empirical research within public economics. Each study applies a distinct methodological approach to a different domain (health, fiscal policy, and local taxation), yet they collectively demonstrate a unifying goal of advancement of credible causal inference through the construction of well-defined counterfactuals. In the first paper, counterfactual modelling uncovers the historical roots of Scotland's life expectancy divergence, revealing long-term structural factors that conventional time-series analysis had obscured. In the second, it is used to isolate the complex economic and social consequences of Ireland's corporate tax undercutting, offering a nuanced perspective on the trade-offs of aggressive fiscal competition. The third moves beyond retrospective evaluation to simulate alternative policy designs, showing how modern valuation and simulation tools can make previously intractable reform scenarios analytically testable. Together, these studies illustrate how counterfactual analysis – once limited to narrow quasi-experimental settings - has matured into a general framework for understanding dynamic policy environments.

This research demonstrates that advancements in counterfactual construction significantly broaden the scope of measurable policy impacts. Synthetic control methods offer a systematic approach for analysing unique or context-specific interventions, while machine learning-driven simulations enable the assessment of prospective policies. By integrating these methodologies, the dissertation combines econometric precision with computational adaptability, showcasing the value of hybrid strategies for deriving robust conclusions in complex, data-intensive settings. The results indicate that counterfactual analysis functions as a comprehensive framework, enhancing the capacity to differentiate genuine structural changes from random fluctuations, accurately assess the duration and persistence of policy effects, and consistently evaluate equity and welfare outcomes using reliable evidence.

The relevance of this research extends beyond the immediate cases under consideration. As data accessibility and computational methodologies continue to progress, counterfactual policy analysis is likely to assume greater importance within economic inquiry and policymaking processes. The capacity to simulate alternative scenarios (assessing potential outcomes across different institutional contexts) remains central to both academic research and applied policy evaluation. Prospective investigations may further incorporate these techniques with real-time administrative datasets, dynamic microsimulation, or structural modelling in order to strengthen causal inference and guide the development of effective policies. This dissertation therefore provides substantive perspectives on key public policy issues while advancing methodological approaches that broaden the capabilities for rigorous causal analysis within complex economic settings.