Effects of Tax Shocks on Inequality: Empirical Evidence from the United Kingdom

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25 January 2025

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This version: January 25, 2025.

Abstract

This study investigates the impact of discretionary tax cuts on income and consumption inequality in the United Kingdom. Using granular survey data from approximately 340,000 households, we construct quarterly inequality measures spanning 1970 to 2020 to assess the heterogeneous effects of exogenous tax shocks on income and consumption distributions. Employing a structural VAR framework, we find that tax cuts increase inequality in the UK. Specifically, a 1 percent tax cut leads to a 2 percent rise in the Gini coefficients of gross income and consumption within a year, with these effects persisting for nearly three years. The rise in inequality is primarily driven by increased labour earnings from full-time and part-time employment among middle- and high-income households, while low-income households experience a slight negative impact due to reduced social security income. Additionally, temporary reductions in VAT induce a short-term decline in CPI inflation, disproportionately boosting consumption among wealthier households. These findings highlight the unequal distributional effects of tax policy and its implications for inequality dynamics.

JEL Classification: C11, D31, E62, H20

Keywords: Tax shocks; income and consumption inequality; Bayesian SVARs.

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1 Introduction

"Even though market forces help shape the degree of inequality, government policies shape those market forces. Much of the inequality that exists today is a result of government policy, both what the government does and what it does not do." (Stiglitz (2012)). This statement highlights the central role of fiscal policy in shaping economic inequality, a relationship explored in this study.

A large body of macroeconomic research examines the impact of fiscal policies on output, growth, and various aspects of economic activity. While fiscal policies can affect income redistribution directly through taxes and transfers, numerous other channels affect inequality indirectly: growth and investment, employment, education, access to technology, and trade policies are only a few.

Empirical findings on the economic impact of taxation vary widely. For example, estimates for the US tax multiplier range from as little as -0.5 in Favero and Giavazzi (2012) to -5 in Romer and Romer (2010). This variation is influenced by several factors, including the objectives of tax reforms, such as financing expenditures, reducing deficits, or addressing recessions, whether tax changes are anticipated or unexpected, their duration, and the degree of progressivity. Additionally, technical aspects, such as the identification strategy for the tax shock, the selected sample period, and the choice of model, significantly affect these estimates.

Tax cuts have been found to increase GDP in the US and UK. Specifically, a one percent tax cut (as a percentage of GDP) boosts GDP by 3 percent over three years in the US (Romer and Romer (2010)) and by 2.5 percent over the same period in the UK (Cloyne (2013)). However, higher output and growth do not necessarily mean lower income inequality. The relationship between growth and inequality has been studied extensively in the literature. Barro (2008) finds the presence of the Kuznets curve across countries and across time. This inverse U-shaped curve indicates that poor countries with a low level of GDP per capita as a starting point may experience rising inequality as their GDP grows but this relationship flattens out and eventually reverses at higher levels of economic development. With this finding in mind, one might expect growth-boosting policies to reduce inequality in a developed economy like the UK. Contrary to this expectation, our findings reveal that tax cuts, while expansionary, exacerbate both income and consumption inequality. Specifically, a tax reduction equivalent to 1 percent of real GDP per capita raises the Gini coefficient of gross income by 2 percent, with this effect persisting for over three years. We observe similar patterns across alternative UK inequality measures.

In this study, we extend Cloyne's (2013) analysis of tax shocks to examine their distributional effects. We construct inequality measures for the UK from 1970 to 2020 using granular survey data from the FES/EFS surveys. Building on Cloyne's (2013) narrative account of UK tax changes in the UK, we identify unanticipated tax shocks and study their impact on inequality measures and other variables of real economic activity. By employing a structural VAR model, we find that a 1 percent tax cut leads to significant increase in the Gini coefficient of gross income in the short run, an effect that persists for several years. Similar results are observed for the Gini coefficient of gross consumption and other inequality measures used for robustness.

The primary contribution of this paper is to provide new insights into the impact of tax policies on inequality. By employing a narrative approach to identify tax shocks and constructing detailed inequality measures using granular data, we can better understand which income and consumption percentiles are most affected and through which transmission channels. Our findings reveal that households above the 90^{th} percentile of income benefit the most from tax cuts, leading to increased inequality primarily in the right tail of the income distribution, while the left tail remains largely unaffected.

The remainder of the paper is organised as follows: Section 2 reviews the existing literature. Section 3 describes the estimation model and identification strategy of the shock. Section 4 presents the quarterly inequality measures as constructed by the EFS survey and the rest of macroeconomic variables. Section 5 presents the dynamic responses of inequality measures to discretionary tax changes, discusses heterogeneity, and investigates channels of transmission. Section 6 addresses robustness issues and alternative experiments. Section 7 concludes.

2 Related Literature

Our work extends the existing literature on the impact of taxation on economic activity by specifically focusing on its distributional effects. We adopt the narrative approach on taxation pioneered by Romer and Romer (2010) for the US and further developed by Cloyne (2013) for the UK to identify exogenous tax changes. This methodology carefully examines each tax change and its underlying motivation, ensuring it is unrelated to current or anticipated economic conditions. This approach establishes the exogeneity of the tax shocks. Romer and Romer (2010) find a significantly higher and more persistent impact of tax shocks compared to some of the previous studies[1]. Their findings indicate that an exogenous tax increase of 1 percent of GDP could lower real GDP by nearly 3 percent over three years, primarily through reduced consumption and investment.

Subsequent research has used this methodology to explore the effects of different types of taxes, such as direct versus indirect taxes (e.g. Nguyen *et al.* (2021)) and personal income versus corporate taxes (e.g. Mertens and Ravn (2013); Cloyne *et al.* (2024)). Additionally, narrative series of tax shocks have been constructed for various countries to estimate their impacts on aggregate variables and growth (e.g. Cloyne (2013) and Cloyne and Hürtgen (2014) for the UK; Hayo and Uhl (2014) for Germany; Pereira and Wemans (2015) for Portugal; Gil *et al.* (2019) for Spain; Hussain and Liu (2024) for Canada; Devries *et al.* (2011) and Guajardo *et al.* (2014) for 17 OECD economies, focused on fiscal consolidations).

While these studies generally do not directly examine the distributional effects of taxation on income, they imply that the composition of tax changes affects different households variably. For example, direct income and corporate tax cuts tend to favour medium and high-income households, whereas reductions in indirect taxes like VAT can positively impact poorer households.

Few studies have specifically addressed the distributional implications of taxation, and these have mostly focused on the United States. Piketty *et al.* (2018) analyse the evolution of income distribution in the US from 1913 to 2014, finding that income for the bottom 50 percent has stagnated, the middle class has experienced moderate growth, and the income of the top 1 percent has surged. The significant increase in top incomes since the late 1990s has largely been driven by gains in capital, which are often taxed at lower rates. The authors note that government's redistribution efforts through taxes and transfers have only modestly mitigated rising inequality. Earlier, Piketty *et al.* (2014) observed that tax cuts for top earners in the US are associated with higher shares of pretax income for top 1 percent, but these do not necessarily boost overall growth. Similarly, Nallareddy *et al.* (2022) find that corporate tax cuts increase inequality in the US by enhancing capital income for top earners, while failing to significantly increase investment.

Thompson and Smeeding (2013) report that taxes and transfers moderated the rise in income inequality in the US during the Great Recession, but mainly benefited elderly

[1]For instance, Blanchard and Perotti (2002) identify a peak-to-impact multiplier of 1.33 percent on GDP, Barro and Redlick (2011) estimate a 1.1 percent effect, Favero and Giavazzi (2012) report 0.5 percent, and Caldara and Kamps (2012) find 0.65 percent. Contrarily, Mountford and Uhlig (2009) report a peak impact of 3.6 percent, aligning more closely with studies that adopted the narrative approach, such as Mertens and Ravn (2014) and Cloyne (2013) for the UK. Ramey (2019) provides a detailed review on tax multipliers.

households and families with children, while wage and hour inequality increased among working-age households. Zidar (2019) finds that tax cuts applied to households in the lower 90 percent of the income distribution increase economic activity and employment in the US. This suggests that tax cuts for lower-income households have a greater economic impact, though their effect on inequality is not directly investigated.

For the UK, studies examining the distributional effects of taxation are sparse. Webber and Thomas (2016) find that the progressivity of direct taxes increased from 1977 to 2015, with their redistributive impact on the Gini coefficient remaining relatively stable, whereas indirect taxes have been consistently regressive, exacerbating income inequality. Ramos and Roca-Sagales (2008) report similar results, indicating that increases in indirect taxes raise income inequality, while the effects of direct taxes are less significant. Gunasinghe *et al.* (2020) present similar findings for Australian tax and spending shocks.

Our approach closely aligns with Ramos and Roca-Sagales (2008) in terms of country and model but diverges in several key aspects. We use a longer and more recent sample, constructing inequality measures at a quarterly frequency rather than using annual data. Moreover, we employ the narrative approach to identify tax shocks while Ramos and Roca-Sagales (2008) and other studies prior to Romer and Romer (2010) often relied on recursive strategies, which may suffer from endogeneity issues. Additionally, we delve into the impacts on various segments of the income distribution, explore transmission channels, and the role of income sources under tax cuts.

3 Empirical Model

To estimate the impact of discretionary tax shocks, we use a structural VAR in the benchmark specification of the following form:

$$Z_t = \begin{pmatrix} f_t \\ y_t \end{pmatrix} = \begin{pmatrix} c_F \\ c_Y \end{pmatrix} + \sum_{j=1}^{P} \begin{pmatrix} B^p_{FF} & B^p_{FY} \\ B^p_{YF} & B^p_{YY} \end{pmatrix} \begin{pmatrix} f_{t-j} \\ y_{t-j} \end{pmatrix} + \begin{pmatrix} u^F_t \\ u^Y_t \end{pmatrix} \tag{1}$$

where $\begin{pmatrix} u^F_t \\ u^Y_t \end{pmatrix} \sim \mathcal{N}(0,\, \Omega)$.

f_t contains the exogenous shock on tax liabilities by the date of implementation as constructed by Cloyne (2013). y_t is the vector of the default macroeconomic variables, which are the log per capita of real GDP, consumption, and investment. The VAR is augmented by the inequality measure which is the log of the Gini coefficient of gross income or consumption respectively at quarter t. c is a vector of constant terms. We estimate the following VAR baseline specification:

$$Z_t = [Tax\ shocks,\ GDP,\ Consumption,\ Investment,\ Gini\ Coefficient] \quad (2)$$

To identify the structural shock, we employ the narrative approach by Romer and Romer (2010) where exogenous tax shocks are defined as the tax policy changes that are not correlated to current and future economic fluctuations. Although proxy VARs are typically used in the literature[2] treating the narrative shock series as the instrumental variable, we follow a simpler and equivalent approach with recursive ordering. We order the discretionary tax shock first in our BVAR. We identify the structural shock through a recursive ordering and by placing it first. As shown in Plagborg-Møller and Wolf (2021), if the instrument is ordered first in a recursive SVAR then the implied impulse responses of the first shock at horizon h are equivalent to the ones generated by a proxy BVAR or an LP-IV model[3]. In the robustness section, we treat the tax shock series as proxy by conducting a proxy BVAR model. The results remain unchanged.

For the estimation, we use a Bayesian approach with Gibbs sampling and a standard Minnesota prior. Four lags are used initially (P=4) to reflect the lag length of Romer and Romer (2010). More lag lengths have been tried in the sensitivity analysis. The sample period is restricted from 1970Q1 to 2009Q4 as the tax shock series are available until 2009. However, we use a longer time span, up to 2020Q1, in the robustness section employing a mixed-frequency BVAR for missing observations. The results remain robust.

4 Data

4.1 Tax shocks

We use the exogenous tax shocks series from Cloyne (2012) from 1970Q1 to 2009Q4. Although the series are available from 1945, the survey from which the inequality measures are derived was not available before 1970[4]. The series of discretionary tax changes fall into

[2]See for example Mertens and Ravn (2013), Nguyen *et al.* (2021), Cloyne *et al.* (2022) for tax shocks in Proxy VARs.

[3]The equivalence between the two identification schemes arises because placing the instrument first in a recursive SVAR satisfies the conditions for a valid instrumental variable: it is contemporaneously correlated with the structural shock of interest and orthogonal to other shocks. This approach isolates the same structural shock by using the Cholesky decomposition of the reduced-form residuals, which is mathematically identical to the projection of residuals onto the instrument in a Proxy SVAR, as demonstrated in Plagborg-Møller and Wolf (2021).

[4]The FES first wave started in 1969 but it has many limitations and therefore we exclude it from our sample.

four categories: long-term improvements in economic performance, ideological beliefs of the ruling party on political or social issues, external pressures imposed by international bodies, and considerations for long-term budget consolidation. Data on UK tax changes come mostly from fiscal events and other narrative sources throughout the year such as the annual Budget event in the spring and the pre-Budget report in the autumn. These events and speeches in the Parliament produce a number of documents with details on tax changes, implementation, scope, and intended revenues[5]. The quarterly series reflect the projected change in tax revenues, normalised by GDP and expressed as a percentage. The implementation date is assigned in the respective quarter if it occurs in the first half of the quarter or in the next one if it takes place in the second half.

4.1.1 Testing for exogeneity of the tax shocks

Cloyne (2013) provides evidence for the exogeneity of the tax shocks series through a Granger causality test and an ordered probit regression. The null hypothesis that all coefficients are equal to zero cannot be rejected. Since we adopt a different identification strategy and model specification, we also check for orthogonality of the estimated tax shock residuals. As in Forni and Gambetti (2014), we perform a Granger causality test by first estimating the structural shocks from the VAR benchmark specification as shown in (2). Then we compute principal components from a UK dataset covering real economic activity, the monetary sector, trade, housing, and prices. We take the residuals corresponding to the first shock (u_t^F) of the benchmark VAR and regress them on the 4 lags of the first 3 principal components which explain more than 80 percent of the underlying data. The p-value is 0.998 and we cannot reject the null hypothesis that all the coefficients in the tax residuals equation are jointly equal to zero. Therefore lagged economic activity, as captured in the principal components, cannot forecast the tax changes.

4.2 Inequality measures and other macroeconomic variables

The measures of inequality are constructed from the household's gross income and total consumption. Both variables come from the Family and Expenditure Survey (FES) (1970-2000), the Expenditure and Food Survey (EFS) until 2008 and the Living Costs and Food Survey (LCFS) thereafter. These surveys are carried out annually and involve, on average, a sample of 7,000 UK households per year[6]. Our sample spans from 1970Q1 to 2020Q1

[5]Examples of these documents are the Financial Statement and Budget Report (FSBR), the Chancellor's budget speech, the Economic and Fiscal Strategy Report (EFSR), White Papers, Economic Surveys and speeches in Parliament as recorded in Hansard.

[6]Further details on these surveys can be found in Theophilopoulou (2022)

and the total number of household observations in our sample period is 343,000.

In these surveys, gross income is defined as the gross normal weekly household income which is the sum of gross wage (from full-time and part-time employment), income from self-employment, social benefits and pensions, investment and rents, and other income sources (code: p344 (1970)). Total consumption is the sum of household expenditure on housing, food, fuel, light, power, clothing, vehicle services, etc. of each household (code: p378 (1970)). Both variables are equivalised taking into account household size. For both variables, we construct the following measures of inequality: the Gini Coefficient, the P90/P10 and the standard deviation of logs. To investigate issues of heterogeneity, we focus on the responses of gross income in the 10^{th}, 50^{th} and 90^{th} percentiles and their components. An important feature of these measures which allows us to study their dynamics in greater detail, is that they are constructed at a quarterly frequency. This is done by assigning each household to the quarter of its interview by the survey (see Cloyne and Surico (2017)).

The three macroeconomic variables in the benchmark specification come from the Office for National Statistics (ONS). They are in constant prices (CMV), seasonally adjusted, and divided by the population. In addition to GDP, consumption is the final household consumption expenditure series in ONS while Investment is the Gross Fixed Capital Formation.

5 The effects of Tax Shocks on Macroeconomy and Inequality

First, we replicate Cloyne's (2013) baseline model using a four-variable VAR. Although Cloyne's time series data is available from 1955, our estimation sample begins in 1970 to align with the availability of inequality variables. Figure 1 presents the results of the subsample using Bayesian estimation. It illustrates the responses of three macroeconomic variables to an anticipated tax cut equivalent to 1 percent of GDP. The shock is clearly expansionary and closely aligns with Cloyne's findings, though the magnitude is smaller due to the different sample period. Specifically, real GDP per capita increases by 1.7%, consumption per capita by around 2.3%, and investment per capita by 3.7% within six quarters.

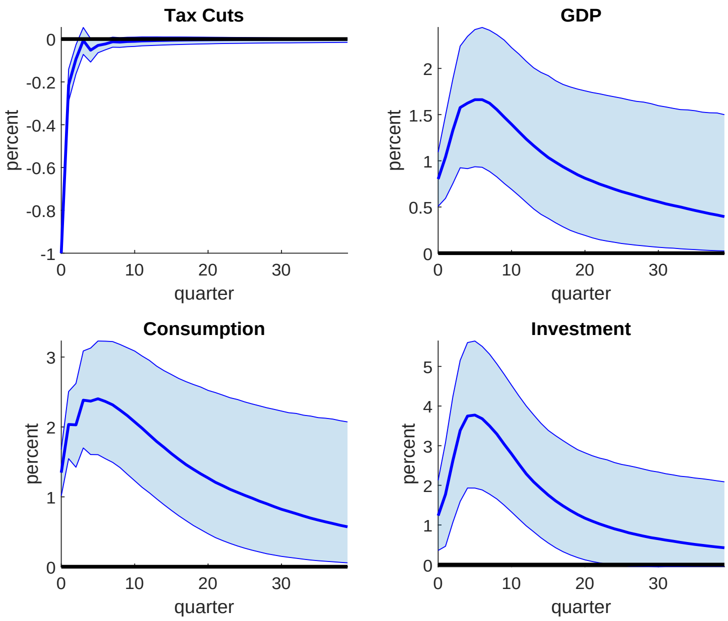

Figure 1: Impulse response functions to a 1 percent tax cut. The vertical axis plots the responses in percent. The horizontal axis indicates time in quarters. The dark blue line represents the median estimate, and the shaded areas indicate the 68% credible intervals.

5.1 Response of Inequality to Tax Shocks

Figure 2 presents the baseline results of the SVAR model described in equation 1. The figure illustrates the responses of key macroeconomic variables and inequality measures to an unanticipated tax cut. The first and second rows display the responses of the Gini coefficients for gross income and consumption, respectively. The responses of real GDP, consumption, and investment per capita all increase following a reduction in the average tax rate, indicating an expansionary effect of this policy. However, inequality also rises to the tax shock, as demonstrated by the Gini coefficients for both income and consumption. Both measures increase by approximately 2% in the third quarter and remain significantly positive for around 3 years. The impact of the tax cuts on inequality measures is therefore both significant and persistent.

5.2 FEVD and HD

The forecast error variance decomposition presented in Figure 3 shows that tax shock plays an important role in the variance of the two inequality measures. Specifically, the contribution of the tax shock to the Gini of gross income is 10.3% after about a year and remains at this level in the long run, while its contribution to the Gini of gross consumption is 5% initially, rising to 9% in the long run.

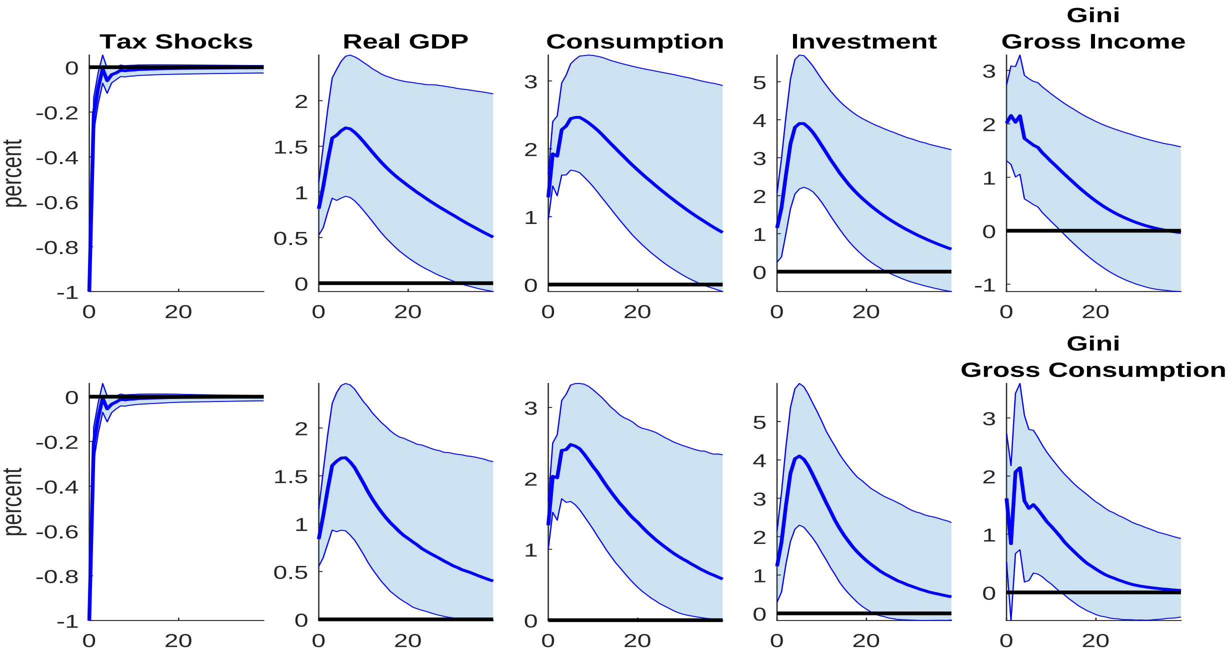

Figure 2: Impulse response functions to a one percent tax cut. The vertical axis plots the responses in percent. The horizontal axis indicates time in quarters. The dark blue line is the median estimate and the shaded areas are the 68% credible intervals.

Next, we ask whether tax shocks alone played a role in the dynamics of income inequality. Figure 4 plots the detrended data on the Gini coefficient of income, alongside the counterfactual in which no other shock occurs during the sample period. This exercise suggests that tax shocks contributed to the fall of inequality around 1980 but increased inequality between 1985-1995. This period was characterised by regressive tax reforms such as cuts in the income tax rates, especially the high ones, and considerable rises in the VAT as the main source of revenue for the government. Moreover, taxes not related to income levels, such as the poll tax, were introduced, further making taxation more regressive.

5.3 Heterogeneous responses and channels of transmission

While the baseline result shows higher inequality in gross income and consumption distributions, it does not specify which parts of these distributions are mostly affected by the tax shock. To investigate this, we augment the baseline specification with the real gross income and consumption at the 10^{th}, 50^{th}, and 90^{th} percentiles respectively, and repeat the main experiment. The responses of these percentiles to a 1% tax cut are reported in Figure 5.

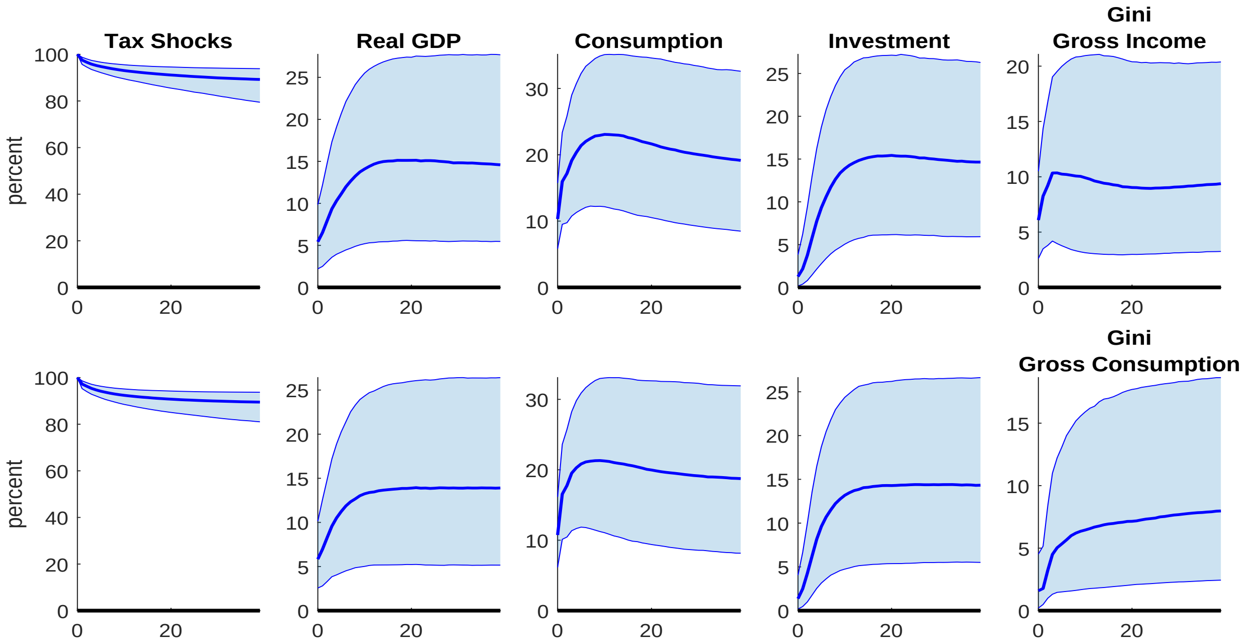

Figure 3: Forecast Error Variance Decomposition to a one percent tax cut. The vertical axis plots the response in percent and the horizontal axis indicates time in quarters. The dark blue line is the median estimate and the shaded areas show the 68% credible intervals.

The largest positive response is observed in the 90^{th} percentile, which jumps by 3% on impact and remains at around 2.5% during the first year following the shock. The response is persistent and the null hypothesis can be rejected for around 7 years. The IRFs of consumption present similar behaviour. Income and consumption at the median percentile also rise, but to a lesser extent. Income in the 10^{th} percentile does not show a significant response to the shock while consumption briefly rises in the impact. By contrast, income at the 10^{th} percentile shows no significant response to the shock, while consumption exhibits a brief initial increase. This exercise demonstrates that the greatest gains in terms of gross income and consumption occur among rich households, whereas poor households remain mostly unaffected, except for a brief initial boost in consumption.

Next, we turn our attention to the factors driving these gains and losses for the three households. First, we examine the components of gross income for the 3 percentiles and how they have evolved over time. Figure 6 shows the main components of gross income for the three income percentiles and their evolution during the sample period. These components include gross wage, other employment income, income from social security, and financial income[7].

[7] A detailed description and definitions of the components of gross income can be found in the Appendix, Table 1.

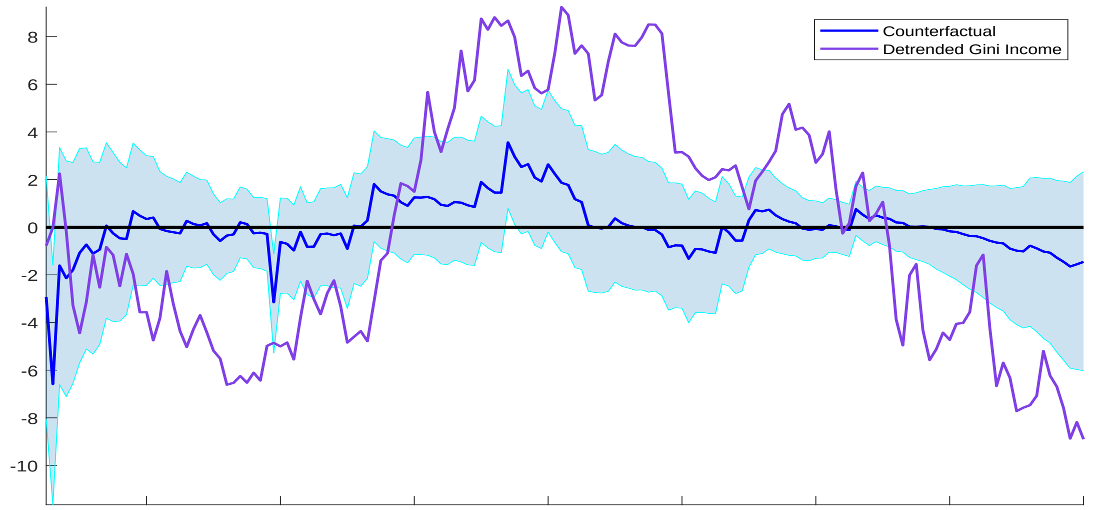

Figure 4: Historical Decomposition of the Gini coefficient of Gross Income. The purple line plots the detrended time series from 1970 to 2010. The blue line is the counterfactual of only tax shocks occurring, The 68% error bands are reported.

Social security benefits, although they have been halved from the mid-1990s toward the end of the sample (from 60% to 30%), remain the second most important source of income for the 10^{th} percentile. In contrast, these benefits constitute a very small share for the median household (less than 5%) and are negligible for high-income households (less than 1%). Gross wages, on the other hand, are the most important income source for all percentiles. They account for more than 80% of total income for the median and high-income households and slightly more than 50% for the low-income household. Other employment income — primarily from self-employment and part-time work — comprises around 20% of the gross income for the 10^{th} percentile and about 10–15% for the median and 90^{th} percentiles. Income from investments (financial income) remains a small proportion for all three percentiles. It is slightly higher for the 90^{th} one but still a very small proportion that can be traced in the data. One reason is that financial income is not stock as wealth is but mostly flows, such as capital gains from assets, dividends, coupons, etc. which represent only a small fraction of the underlying wealth. Another reason is, of course, misreporting and inaccurate estimation of this source in surveys [8].

The next step involves estimating the responses of these income sources to tax shocks. We repeat the baseline estimation but now we substitute the inequality variable with the three percentiles for each component. Figure 7 presents IRFs to 1% reduction of taxes as

[8] A discussion about the limitations of the FES/EFS/LCF surveys can be found in Theophilopoulou (2022).

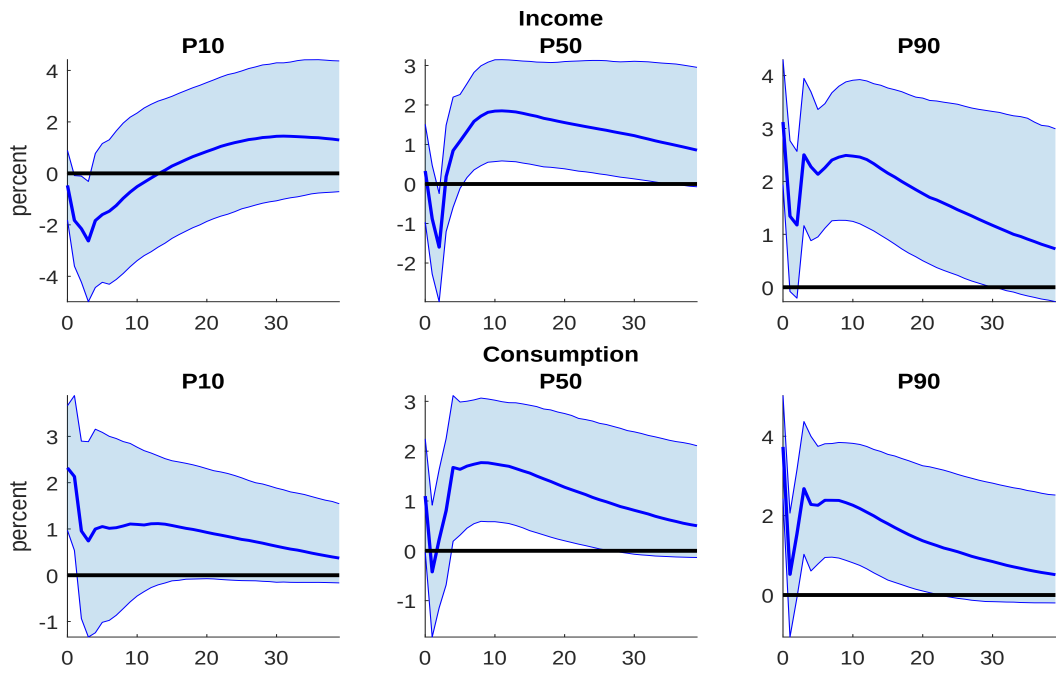

Figure 5: Impulse response functions of gross income and consumption percentiles to a one percent tax cut. The vertical axis plots the response in percent. The horizontal axis indicates time in quarters. The dark blue line is the median estimate and the shaded areas are the 68% error bands.

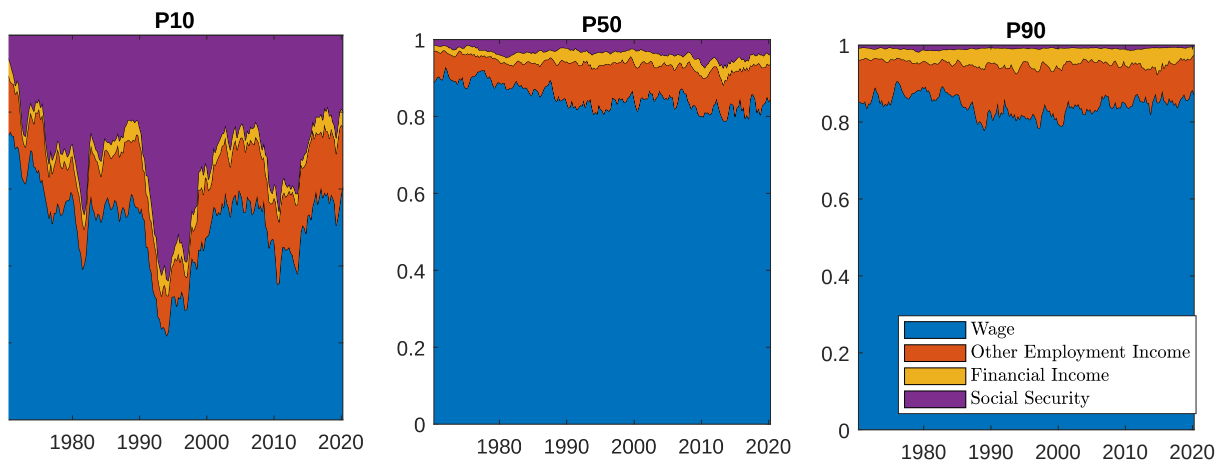

Figure 6: Main components of gross income for households in the 0-10th (left), 40th-50th (middle), and above the 90th (right) percentiles.

a percentage of GDP for each of the 3 representative percentiles in each component. The main observation is that 3 out of 4 components of the 90th percentile respond significantly to tax cuts, which explains why this percentile is most affected. Its income from wages and self-employment rises as this household has now a higher incentive to increase labour

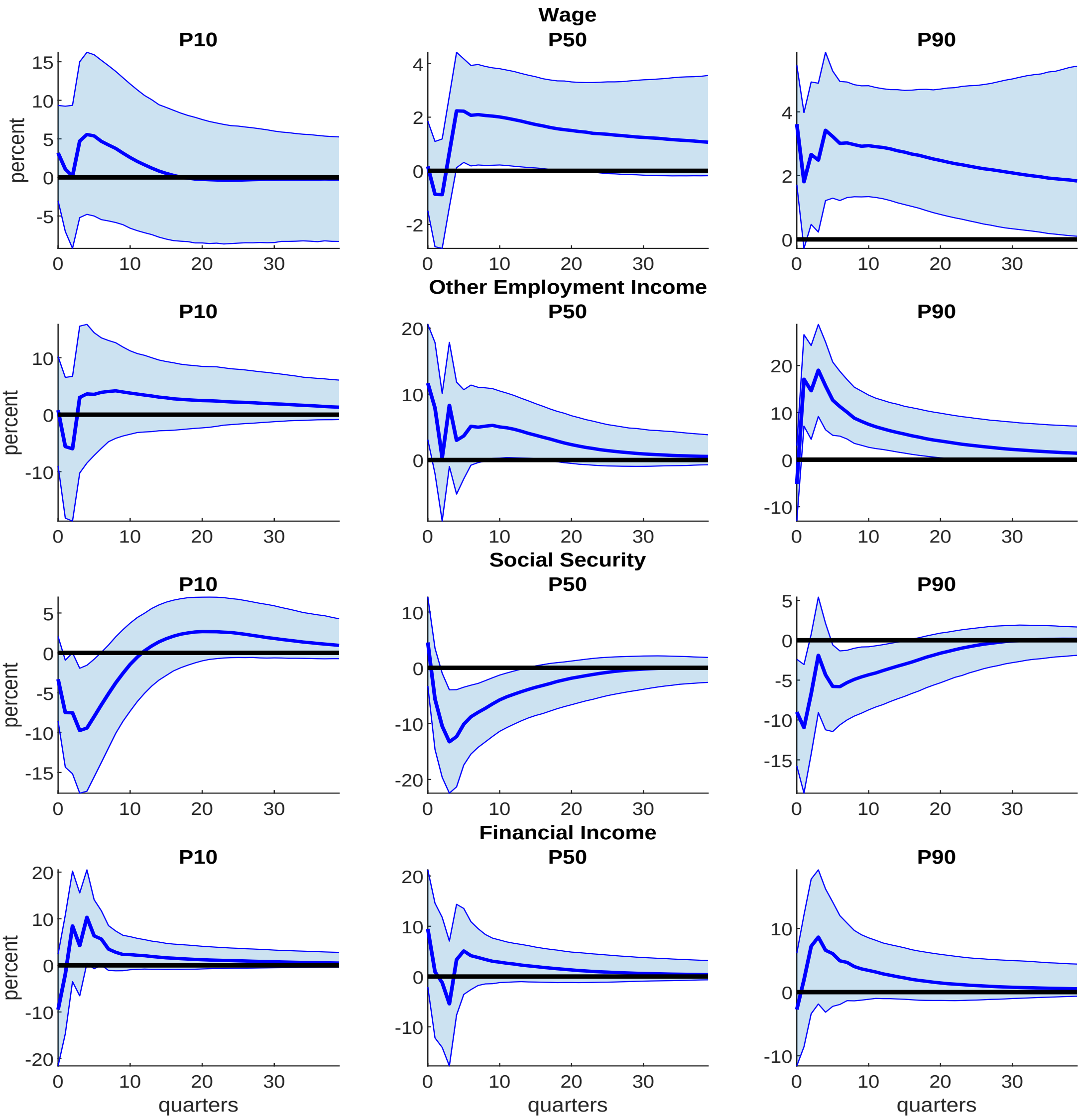

Figure 7: Impulse response functions of gross income components to a tax cut of one percent of GDP, for households in the 10$^{\text{th}}$, 50$^{\text{th}}$, and 90$^{\text{th}}$ percentiles of the income distribution.

supply and hours worked. Its social security income falls, which is true for all three, however in this case the proportion is negligible. Financial income rises but we cannot reject the null hypothesis. This holds for all three percentiles.

The median household experiences a slight rise in its wage income while the response of other sources of employment is not significant. A possible reason is that income from other sources is not highly taxable in this category, therefore the incentive to increase it is moderate. Income from social security falls which can be a combination of both higher wage income for the household and less tax revenues for the government.

The most striking income component response for the poor household is the drop of social security by 10% on its peak. This can be for the reasons mentioned above. While this source of income is not of major importance for the other two households, is the second largest for the low-income household. Thus, this can be another factor that amplifies income inequality.

Overall, social security benefits appear to decline across all percentiles, with the 50^{th} percentile showing the most pronounced response. This outcome may result from higher economic activity, reducing the need for unemployment benefits and other transfers, particularly for median and wealthy households. However, lower tax revenues may also contribute to reduced benefits. In line with studies that fail to support the "starve the beast" hypothesis (e.g., Romer and Romer (2009)), we similarly do not find evidence of reduced government spending. Figure 8 illustrates the results of a larger VAR, which includes government consumption, a short-term interest rate, CPI inflation, and FTSEALL returns alongside the benchmark variables. Final government consumption appears to increase, reflecting the expansionary trend in other macroeconomic variables.

Wages from main occupation and part-time jobs rise for all percentiles with the 90^{th} percentile to show the highest significant rise and the 10^{th} one the lowest and not significant. Higher wage income can come from higher GDP, consumption and investment. (Figures 2 and 8). Another important channel seems to be the inflation one. Lower prices (e.g. from temporary VAT cuts) boost consumption in all percentiles (Figure 2) with the highest rise in the 90^{th} percentile and the lowest in the 10^{th}. The financial channel does not seem to play a role. The IRFs of FTSEALL returns is not significantly different from zero (Figure 8) which agrees with the responses of financial income in all percentiles (Figure 7).

5.4 Heterogeneous Responses in the Labour Market

Looking at the response of the average gross wage, we observe a significant increase to the expansionary tax shock (see Appendix, Figure A1). This rise is evident across all three percentiles, with the largest gains observed in the 50^{th} and 90^{th} percentiles (see Figure 7, first row). However, this increase is not reflected in working hours. Total usual weekly hours (from main occupation) show only a small and statistically insignificant rise. Specifically, while weekly hours increase modestly in the 10^{th} and 50^{th} percentiles, these responses are not statistically significant (see Figure 9). In contrast, hours for households in the 90^{th} percentile decrease by nearly 4%. This pattern suggests that, within the UK labour market, households in the 90^{th} percentile benefit the most from the tax cuts. They

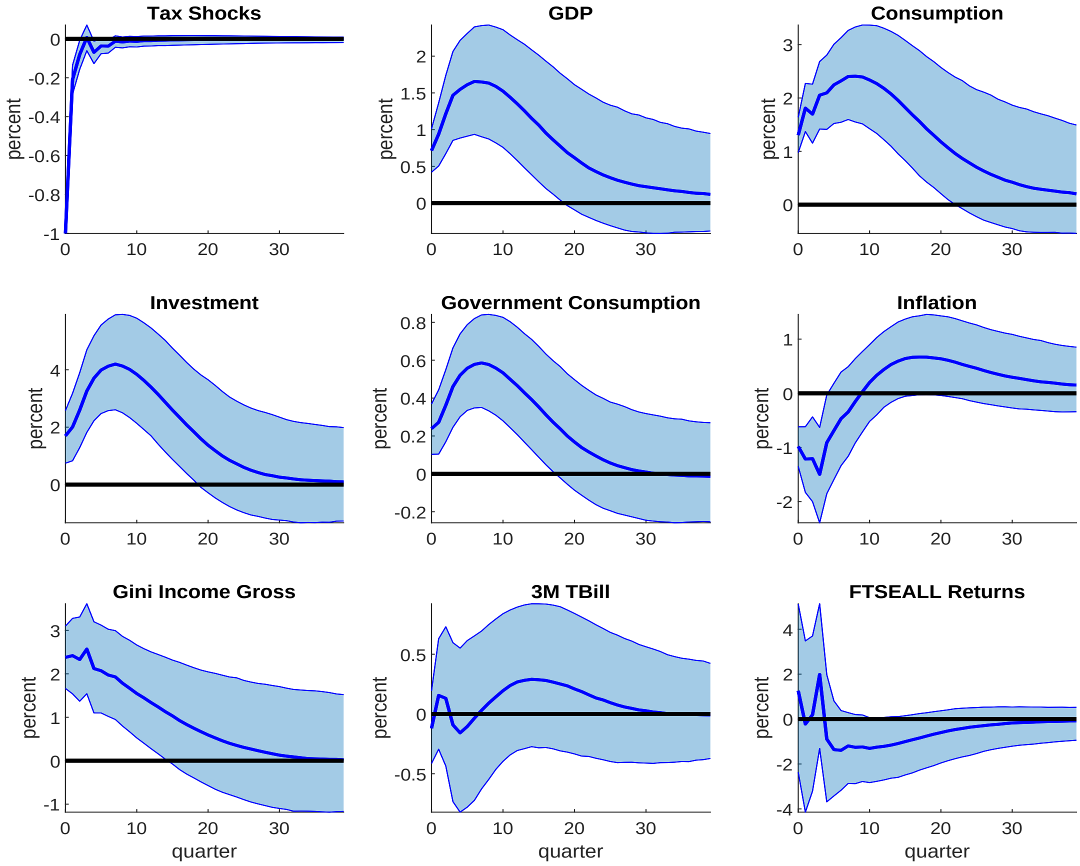

Figure 8: Impulse response functions of macroeconomic variables to a tax cut of one percent of GDP.

experience higher gross wages while simultaneously working fewer weekly hours, likely reflecting a strong income effect.

Linking our findings to Cloyne's (2013) discussion on the impact of tax cuts on the labour market, we observe a neoclassical response in real gross wages across all percentiles, while the response in working hours is heterogeneous. For households in the 10th and 50th percentiles, the substitution effect dominates, leading to an increase in working hours. In contrast, high-income households (90th percentile) experience a pronounced income effect, resulting in a reduction in working hours. High-income earners may choose to work less when their after-tax income increases, as they can afford to allocate more time to leisure.

Saez (2001) highlights that the income effect can be particularly significant for high earners, potentially reducing labour supply following tax cuts, as these individuals prioritise leisure over additional income. Similarly, Zidar (2019) finds that tax cuts have a negligible and statistically insignificant impact on employment growth, including hours worked and participation rates, for the top 10% of earners.

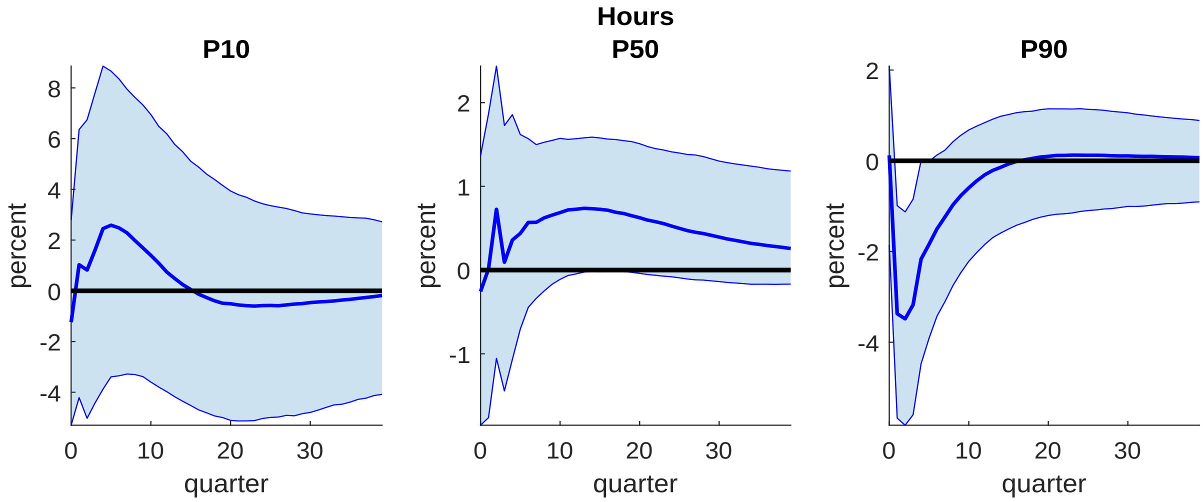

Figure 9: Impulse response functions of usual weekly hours to a tax cut of one percent of GDP, for households in the 10^{th}, 50^{th}, and 90^{th} percentiles of the income distribution.

6 Robustness

To assess the robustness of our findings, we examine three key aspects: model specifications, dataset variations, and identification strategies. Despite exploring various modifications, our benchmark results remain consistent across all scenarios. While some minor variations in magnitude are observed, all experiments uniformly indicate an increase in inequality measures in response to discretionary tax shocks.

6.1 Model specification

In this section, we explore different model specifications by varying the number of variables included, lag lengths, and extending the sample's time span.

Number of variables First, we introduce government's final consumption to examine whether it decreases due to tax cuts, i.e. to check the "starve the beast" hypothesis. If government expenditure, which includes social security funds, does decrease, it could significantly impact lower-income households, which heavily rely on benefits. In line with the findings of Romer and Romer (2010) and Cloyne (2013), we observe a positive response of government spending to tax shocks (Figure 8). This finding aligns with the hypothesis that reductions in benefits observed for the 10^{th} percentile of income are associated with higher employment and wages, indicative of an expansionary fiscal shock.

To address the impact of monetary policy shocks, their interaction with fiscal policy, and their contribution to inequality[9], we include the 3-month Treasury Bill rate in our analysis[10]. Furthermore, we include the growth rate of the Consumer Price Index (CPI) to capture inflation shocks, which have substantial ramifications for the income and consumption levels of low-income households. For example, recent fiscal measures within the European Union have targeted mitigating the adverse effects of rising energy prices on disadvantaged households, through mechanisms such as price regulation or consumption subsidies, as highlighted in the study by Charalampakis *et al.* (2022). Our analysis does not reveal any significant response of the short-term interest rate, suggesting the absence of crowding-out effects. However, we do observe a decrease in the inflation rate in the short term, which potentially stimulates real income and consumption levels.

The inclusion of FTSEALL returns serves to account for financial shocks and capture the interplay between fiscal policy and stock market prices. Research, such as that conducted by Mumtaz and Theodoridis (2020), indicates that the direction and extent of stock price responses to fiscal stimuli hinge on various factors. These include their influence on real interest rates, public debt levels, growth expectations, and the specific composition of the tax cuts, such as whether they are lump sum, targeted at income, or directed towards capital. In our analysis, we do not find any significant response of FTSEALL returns to the tax shock, which aligns with our previous findings on the response of financial income for the three percentiles.

Lag Length In our benchmark model, the lag length is set to 4, in line with the approach taken by Cloyne (2013). However, recognising that this may not be optimal according to model selection criteria, we also explore alternatives suggested by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which recommend 2 and 1 lags, respectively. Additionally, we investigate a longer lag length of 12, as proposed by Romer and Romer (2010) to capture any delayed or long-run effects of the dependent variables. The response of the Gini coefficient, as it can be seen in the first row of Figure 10, remains consistent across all specifications, with the maximum response observed at 2% in the 12-lag model.

Sample period In this robustness check, the sample period for estimation is extended beyond the baseline period to cover until 2020Q1, even though the instrument's data is only available until 2009Q4. The extension of the sample period allows for an assessment

[9]Studies by Colciago *et al.* (2019) and McKay and Wolf (2023) summarise research on this topic.
[10]Similar results are obtained when using the Bank of England's policy rate.

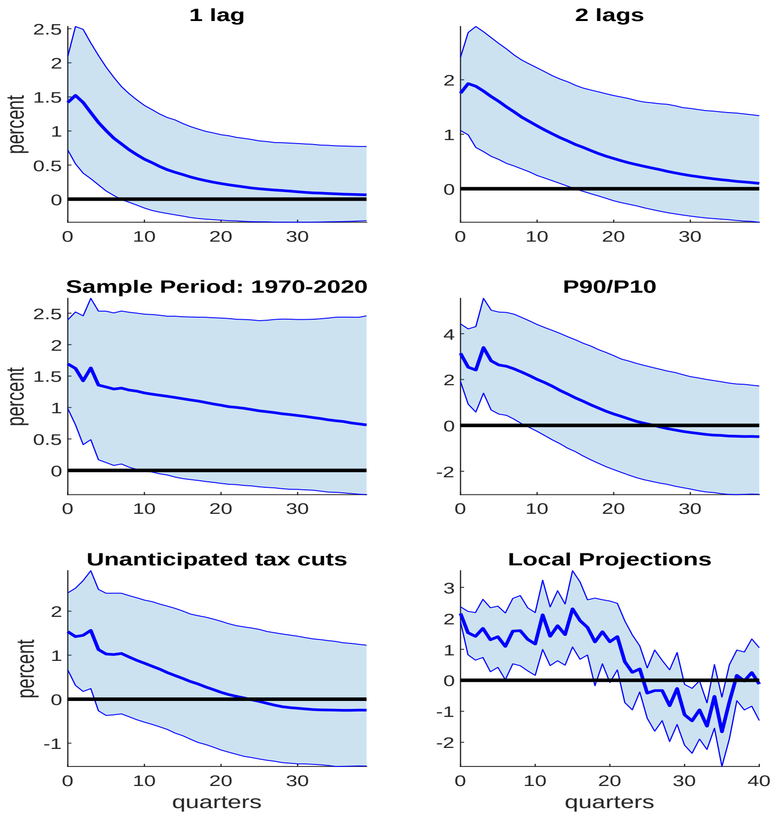

Figure 10: Robustness checks: Responses of Gini Coefficient of gross income to a tax cut of one percent of GDP across various model specifications.

of how the results of the baseline specification hold up over a longer time span. To estimate the VAR model for this extended period, the Gibbs sampling algorithm is utilized, treating the missing observations in the instrument as additional state variables. As in Jarociński and Karadi (2020), the simulation smoother proposed by Durbin and Koopman (2002) is employed to draw the missing observations from the posterior distribution. Conditional on this draw, the posterior distribution of the VAR coefficients and residuals covariance are standard and given by the normal and inverted Wishart (IW) distributions, respectively. Similar to the baseline specification, the identification of the shock is conducted using Cholesky decomposition. The results are presented in the second row of Figure 10, which shows that the response of the Gini coefficient for income is very similar to the benchmark result. However, the error bands are larger due to the increased complexity of the model. Additionally, the peak response is slightly lower, but the shock is more persistent in affecting inequality over the extended sample period.

6.2 Data

In this section, we approach the analysis of income and consumption distributions from a different angle, employing both the standard deviation of logs of household income and the ratio of the 90^{th} and 10^{th} percentiles. Additionally, we use a time series exclusively comprising unanticipated tax shocks to address expectations.

Measures of inequality As the Gini coefficient is less sensitive to changes in the tails of the income distribution and reflects mostly changes in the middle, it may fail to capture shifts of inequality in the extremes. To address this, we use the ratio of the 90^{th} to 10^{th} percentile (P90/P10) of gross income, which provides valuable insights, especially when policies predominantly impact high-income households while also affecting the broader population. In contrast, the standard deviation of logs is less influenced by extreme values and outliers. The impulse response functions (IRFs) of both measures to a tax shock are depicted in the second row of Figure 10. Both measures exhibit an increase in response to the tax shock, with the P90/P10 ratio showing a notably stronger reaction compared to the standard deviation of logs. This suggests that the impact of the tax shock is stronger in the tails of the income distribution relative to the central percentiles.

Unanticipated tax shocks Given that the implementation of a tax policy typically follows its announcement date, agents may have adjusted their behaviour by its implementation date, especially if the two dates are far from each other. Consequently, the implementation of tax change may no longer be perceived as a shock. To address this concern, Mertens and Ravn (2012) and Cloyne (2013) define a surprise tax shock as one implemented within a single quarter (90 days) of the announcement date, ensuring that announcement and implementation occur in the same quarter. As demonstrated by Cloyne (2013), the majority of changes fall within this category, indicating rapid implementation that qualifies as surprise shocks. We replicate the benchmark experiment using the time series of surprise tax cuts, which comprises slightly fewer observations. The results are displayed in the last row of Figure 10. While the response mirrors the baseline for the initial impact, it exhibits a shorter duration and less persistence.

6.3 Identification strategy

To address Ramey (2016) caution regarding the potential endogeneity of fiscal shocks identified through narrative evidence, as for example tax cuts can be associated with pessimistic economic outlooks, we adopt a strategy in which we use the narrative tax cuts as an instrument within a Proxy VAR framework to identify tax shocks. While acknowledging that these series may contain some noise or measurement errors, they provide a rich information set derived from narrative accounts. Therefore, given that they satisfy the relevance condition with the structural tax shock and exogeneity condition with all other shocks, this narrative series qualifies as a valid instrument. We introduce a new variable, the average tax rate, in the benchmark specification. This variable is constructed by dividing aggregate real tax receipts at time t by real GDP at time t, following the approach of Nguyen *et al.* (2021). The response of the Gini coefficient to a cut in the average tax rate is depicted in the last panel of Figure 10. On impact, the Gini coefficient increases, and although the magnitude appears to be smaller compared to the baseline identification, it exhibits considerable persistence.

6.4 Estimation technique

To address potential mis-specification concerns in the VAR model, we adopt Jordà (2005) local projection method for generating impulse responses. The Gini coefficient's response is displayed in the last row of Figure 10. Its magnitude and persistence closely resemble those of the baseline specification, suggesting that the baseline SVAR provides a robust approximation of the true model. However, the response exhibits slightly more volatility, likely due to the LP method's fewer restrictions.

7 Conclusions

The macroeconomic effects of tax changes have sparked considerable debate, largely due to the unclear exogeneity of tax shocks. This paper utilises Cloyne's (2013) construction discretionary tax shocks in the UK to delve deeper into their impact on inequality.

Taxation is a fundamental policy tool aimed at mitigating inequalities and providing a safety net. However, the effects of discretionary tax cuts, though often deemed expansionary, can have different implications for households with varying income and consumption profiles, stemming from diverse transmission mechanisms. Employing a series of VAR models, we find that tax cuts rise inequality measures in the UK, including the Gini coefficient, standard deviation of logs, and the P90/P10 ratios, upon impact, with persistent positive and significant effects in the medium term. Further analysis via forecast error variance decomposition (FEVD) highlights the substantial role of tax shocks in Gini coefficient volatility. Additionally, historical decomposition suggests that while tax shocks may have negatively impacted the Gini prior to 1980, they contributed positively to it after 1985.

The impact is observed to be higher in the right tail of the income and consumption distributions as it benefits more the high income households. Notably, the 90^{th} percentile of income shows to have the higher response to the shock. Income decomposition reveals that wages and self-employment income experience the most substantial increase in the high income percentile, while social benefits, crucial for low-income households, decline.

While the effect on consumption inequality may be less pronounced, there is still evidence to suggest that temporary declines in inflation, such as those resulting from VAT cuts, can stimulate the consumption of middle- and higher-income percentiles. Conversely, while the consumption levels of poorer households briefly increase on impact, this response is short-lived and largely insignificant overall.

References

Barro, Robert J., 2008, Inequality and Growth Revisited, *Working Papers on Regional Economic Integration 11*, Asian Development Bank.

Barro, Robert J and Charles J Redlick, 2011, Macroeconomic effects from government purchases and taxes, *The Quarterly Journal of Economics* **126**(1), 51–102.

Blanchard, Olivier and Roberto Perotti, 2002, An empirical characterization of the dynamic effects of changes in government spending and taxes on output, *The Quarterly Journal of Economics* **117**(4), 1329–1368.

Caldara, Dario and Christophe Kamps, 2012, The analytics of fiscal multipliers and the effectiveness of fiscal policies, *Economic Journal* **122**(563), F540–F561.

Charalampakis, Evangelos, Bruno Fagandini, Lukas Henkel and Chiara Osbat, 2022, The impact of the recent rise in inflation on low-income households, *ECB Economic Bulletin* **7**, 4. Published as part of the ECB Economic Bulletin, Issue 7/2022.

Cloyne, James, 2013, Discretionary tax changes and the macroeconomy: new narrative evidence from the United Kingdom, *American Economic Review* **103**(4), 1507–1528.

Cloyne, James, Joseba Martinez, Haroon Mumtaz and Paolo Surico, 2022, Short-Term Tax Cuts, Long-Term Stimulus, *NBER Working Papers 30246*, National Bureau of Economic Research, Inc.

Cloyne, James, Joseba Martinez, Haroon Mumtaz and Paolo Surico, 2024, Taxes, Innovation and Productivity, *Working Papers 979*, Queen Mary University of London, School of Economics and Finance.

Cloyne, James and Patrick Hürtgen, 2014, The macroeconomic effects of monetary policy: a new measure for the United Kingdom.

Cloyne, James S, 2012, Discretionary tax shocks in the United Kingdom 1945-2009: a narrative account and dataset.

Cloyne, James S and Paolo Surico, 2017, Household debt and the dynamic effects of income tax changes, *The Review of Economic Studies* **84**(1), 45–81.

Colciago, Andrea, Anna Samarina and Jakob de Haan, 2019, Central Bank Policies and Income and Wealth Inequality: A Survey, *Journal of Economic Surveys* **33**(4), 1199–1231.

Devries, Pete, Jaime Guajardo, Daniel Leigh and Andrea Pescatori, 2011, A Tale of Two Depressions, *IMF Economic Review* **59**(1), 49–87.

Durbin, James and Siem Jan Koopman, 2002, A Simple and Efficient Simulation Smoother for State Space Time Series Analysis, *Biometrika* **89**(3), 603–615.

Favero, Carlo and Francesco Giavazzi, 2012, Measuring tax multipliers: The narrative method in fiscal VARs, *American Economic Journal: Economic Policy* **4**(2), 69–94.

Forni, Mario and Luca Gambetti, 2014, Sufficient information in structural VARs, *Journal of Monetary Economics* **66**, 124–136.

Gil, Paula, Francisco Martí, Richard Morris, Javier J Pérez and Roberto Ramos, 2019, The output effects of tax changes: narrative evidence from Spain, *SERIEs* **10**, 1–23.

Guajardo, Jaime, Daniel Leigh and Andrea Pescatori, 2014, Expansionary austerity? International evidence, *Journal of the European Economic Association* **12**(4), 949–968.

Gunasinghe, Chandika, EA Selvanathan, Athula Naranpanawa and John Forster, 2020, The impact of fiscal shocks on real GDP and income inequality: What do Australian data say?, *Journal of Policy Modeling* **42**(2), 250–270.

Hayo, Bernd and Matthias Uhl, 2014, The macroeconomic effects of legislated tax changes in Germany, *Oxford Economic Papers* **66**(2), 397–418.

Hussain, Syed M and Lin Liu, 2024, Macroeconomic effects of discretionary tax changes in Canada: Evidence from a new narrative measure of tax shocks, *Canadian Journal of Economics/Revue canadienne d'économique* **57**(1), 78–107.

Jarociński, Marek and Peter Karadi, 2020, Deconstructing monetary policy surprises—the role of information shocks, *American Economic Journal: Macroeconomics* **12**(2), 1–43.

Jordà, Òscar, 2005, Estimation and Inference of Impulse Responses by Local Projections, *American Economic Review* **95**(1), 161–182.

McKay, Alisdair and Christian K. Wolf, 2023, Monetary Policy and Inequality, *Journal of Economic Perspectives* **37**(1), 121–144.

Mertens, Karel and Morten O Ravn, 2012, Empirical evidence on the aggregate effects of anticipated and unanticipated US tax policy shocks, *American Economic Journal: Economic Policy* **4**(2), 145–181.

Mertens, Karel and Morten O Ravn, 2013, The dynamic effects of personal and corporate income tax changes in the United States, *American economic review* **103**(4), 1212–1247.

Mertens, Karel and Morten O Ravn, 2014, A reconciliation of SVAR and narrative estimates of tax multipliers, *Journal of Monetary Economics* **68**, S1–S19.

Mountford, Andrew and Harald Uhlig, 2009, What are the effects of fiscal policy shocks?, *Journal of applied econometrics* **24**(6), 960–992.

Mumtaz, Haroon and Konstantinos Theodoridis, 2020, Fiscal policy shocks and stock prices in the United States, *European Economic Review* **129**(C).

Nallareddy, Suresh, Ethan Rouen and Juan Carlos Suárez Serrato, 2022, Do corporate tax cuts increase income inequality?, *Tax Policy and the Economy* **36**(1), 35–91.

Nguyen, Anh DM, Luisanna Onnis and Raffaele Rossi, 2021, The macroeconomic effects of income and consumption tax changes, *American Economic Journal: Economic Policy* **13**(2), 439–466.

Pereira, Manuel Coutinho and Lara Wemans, 2015, Output effects of a measure of tax shocks based on changes in legislation for Portugal, *Hacienda Pública Española* (215), 27.

Piketty, Thomas, Emmanuel Saez and Gabriel Zucman, 2018, Distributional national accounts: methods and estimates for the United States, *The Quarterly Journal of Economics* **133**(2), 553–609.

Piketty, Thomas, Emmanuel Saez and Stefanie Stantcheva, 2014, Optimal taxation of top labor incomes: A tale of three elasticities, *American economic journal: economic policy* **6**(1), 230–271.

Plagborg-Møller, Mikkel and Christian K. Wolf, 2021, Local Projections and VARs Estimate the Same Impulse Responses, *Econometrica* **89**(2), 955–980.

Ramey, V.A., 2016, Chapter 2 - Macroeconomic Shocks and Their Propagation, Vol. 2 of *Handbook of Macroeconomics*, Elsevier, pp. 71–162.

Ramey, Valerie A., 2019, Ten Years After the Financial Crisis: What Have We Learned from the Renaissance in Fiscal Research?, *Journal of Economic Perspectives* **33**(2), 89–114.

Ramos, Xavier and Oriol Roca-Sagales, 2008, Long-Term Effects of Fiscal Policy on the Size and Distribution of the Pie in the UK, *Fiscal Studies* **29**(3), 387–411.

Romer, Christina D. and David H. Romer, 2009, Do Tax Cuts Starve the Beast? The Effect of Tax Changes on Government Spending, *Brookings Papers on Economic Activity* **2009**, 139–200.

Romer, Christina D and David H Romer, 2010, The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks, *American Economic Review* **100**(3), 763–801.

Saez, Emmanuel, 2001, Using Elasticities to Derive Optimal Income Tax Rates, *The Review of Economic Studies* **68**(1), 205–229.

Stiglitz, Joseph E, 2012, *The price of inequality: How today's divided society endangers our future*, WW Norton & Company.

Theophilopoulou, Angeliki, 2022, The impact of macroeconomic uncertainty on inequality: An empirical study for the United Kingdom, *Journal of Money, Credit and Banking* **54**(4), 859–884.

Thompson, Jeffrey P and Timothy M Tim Smeeding, 2013, Inequality and poverty in the United States: the aftermath of the Great Recession.

Webber, David and Nathan Thomas, 2016, The effects of taxes and benefits on income inequality: 1977 to financial year ending 2015, *Technical report*, Office for National Statistics.

Zidar, Owen, 2019, Tax cuts for whom? Heterogeneous effects of income tax changes on growth and employment, *Journal of Political Economy* **127**(3), 1437–1472.

Appendix: Data and gross income components

Definitions and sources of the macroeconomic data, the inequality measures, the income components, the financial data as well as other data used for this paper are illustrated in Table 1. All macrovariables are expressed in real terms, seasonally adjusted and divided by population. The inequality measures are also seasonally adjusted. The income decomposition components are in real per capita terms divided by GDP deflator and seasonally adjusted. All of the aforementioned data is transformed in logs times 100. The real average tax rate variable is the sum of nominal tax and national income receipts divided by GDP deflator and it is expressed as a percentage of real GDP.

Table 1: DATA SOURCES AND DEFINITIONS

Series	Description	Source	Code
	Fiscal Data		
Tax Shocks	Narrative Exogenous Tax Cuts	Cloyne (2013)	
Unanticipated Tax Shocks	Narrative Exogenous Tax Cuts implemented within one quarter from the announcement date (Mertens and Ravn (2012))	Cloyne (2013)	
	Inequality Data		
	Gross Income		
Gini coefficient	Inequality measure of normal Gross household income	FES/LCFS	
P90/P10	Inequality measure of normal Gross household income	FES/LCFS	
Standard Deviation of log levels	Inequality measure of normal Gross household income	FES/LCFS	
	Gross Consumption		
Gini coefficient	Inequality measure of total household consumption	FES/LCFS	
P90/P10	Inequality measure of total household consumption	FES/LCFS	
Standard Deviation of log levels	Inequality measure of total household consumption	FES/LCFS	
	Income Decomposition Components		
Wage	Real Normal gross wage/salary, 13-week rule applied	FES/LCFS	
Other Employment Income	Real Gross wage salary last time paid (subsidiary occupation) + Income from subsidiary self-employment + Income from self-employment (main or only occupation)	FES/LCFS	
Financial Income	Real Income from pensions, annuities and investments	FES/LCFS	
Social Security	Real Social security benefits included in income calculations	FES/LCFS	
	Macroeconomic and Financial Data		
GDP	Real Gross Domestic Product per-capita, SA	ONS	ABMI divided by population
Consumption	Real Household Final Consumption Expenditure per-capita, SA	ONS	ABJR divided by population

Table 1: DATA SOURCES AND DEFINITIONS

Macroeconomic and Financial Data (continued)			
Investment	Real Total Gross Fixed Capital Formation per-capita, SA	ONS	NPQT divided by population
Government Consumption	General Govrn: Real Final Consumption Expenditure per-capita, SA	ONS	NMRY divided by population
Average Tax Rate	Aggregate Real Tax and NI Receipts divided by Real GDP, SA	ONS	[(NMBY+NMCU +LIQR+AIIH) /L8GG]/ ABMI
Policy Rate	Bank of England Base Rate	BOE	Official bank rate history
Inflation	Change in retail price index (RPI)	ONS	CZBH
CPI	Consumer Price Index		
GFCF	Gross Fixed Capital Formation		
RIMP	Real Imports		
REXP	Real Exports		
UR	Unemployment Rate		
NEER	Nominal Effective Exchange Rate		
IOP	Index of Production		
STP	Stock Prices		
STI	Short-term Interest Rate		
LTI	Long-term Interest Rate		
HOUSEP	House Price Index		
CREDIT	Credit to Private Sector		
NARROWM	Narrow Money		
BROADM	Broad Money		
GDP Deflator	Implied GDP deflator at market prices: SA Index	ONS	L8GG
FTSEALL Return	3-Month or 90-day Rates and Yields: Treasury Securities for the United Kingdom	FRED	IR3TTS01GBQ156N
Hours	Normally weekly household hours worked (main occupation)	FES/LCFS	
Participation rate	The ratio of labour force to the working age population, aged 16-64	ONS	(LF2G+LF2I)/LF2O
Population	UK resident population: mid-year estimates	ONS	EBAQ

Estimation Algorithm for Bayesian VAR

The estimation algorithm for the Bayesian SVAR model presented in (1) and the use of Gibbs Sampling are well-known and standard techniques. For convenience, we summarise the process here. Interested readers can refer to Koop (2003), Kadiyala and Karlsson (1997), or Uhlig (2005) for more detailed explanations.

The benchmark specification in (1) in the main paper can be expressed as:

$$Z_t = c + \sum_{j=1}^{P} B_j Z_{t-j} + v_t, \tag{A1}$$

where $v_t \sim N(0, \Omega)$. Following Uhlig (2005), we use Gibbs sampling to draw from the posterior distribution of the VAR coefficients, assuming flat priors.

The model can be written compactly as:

$$Y_t = X_t B + v_t, \tag{A2}$$

with $Y_t = Z_t$ and $X_t = [c_i, Y_{t-1}, \ldots, Y_{t-p}]$. It can be re-written as:

$$y = (I_N \otimes X)b + V, \tag{A3}$$

where $y = \text{vec}(Y_t)$, $b = \text{vec}(B)$, and $V = \text{vec}(v_t)$.

Assuming a normal prior for the VAR coefficients:

$$p(b) \sim N(b_0, H), \tag{A4}$$

where b_0 is the prior mean vector and H is the prior covariance matrix.

The posterior distribution of the VAR coefficients conditional on Σ is normal:

$$H(b|\Sigma, Y_t) \sim N(M^*, V^*), \tag{A5}$$

where:

$$M^* = (H^{-1} + \Sigma^{-1} \otimes X_t' X_t)^{-1}(H^{-1} b_0 + \Sigma^{-1} \otimes X_t' X_t \hat{b}), \tag{A6}$$

$$V^* = (H^{-1} + \Sigma^{-1} \otimes X_t' X_t)^{-1}. \tag{A7}$$

The prior for the VAR covariance matrix is inverse Wishart:

$$p(\Sigma) \sim IW(S, \alpha), \tag{A8}$$

with the posterior conditional on b:

$$H(\Sigma|b, Y_t) \sim IW(\Sigma, T+\alpha), \tag{A9}$$

where:

$$\Sigma = S + (Y_t - X_t B)'(Y_t - X_t B). \tag{A10}$$

Gibbs Sampling Algorithm

1. **Set priors** for the VAR coefficients $p(b) \sim N(b_0, H)$ and the covariance matrix $p(\Sigma) \sim IW(S, \alpha)$. Initialise Σ (e.g., using OLS estimates).

2. **Sample VAR coefficients** from the following conditional posterior distribution:

$$H(b|\Sigma, Y_t) \sim N(M^*, V^*), \tag{A11}$$

   where M^* and V^* are as defined above.

3. **Draw** Σ from its conditional distribution:

$$H(\Sigma|b, Y_t) \sim IW(\Sigma, T+\alpha), \tag{A13}$$

   where $\Sigma = S + (Y_t - X_t B^{(1)})'(Y_t - X_t B^{(1)})$ and $B^{(1)}$ is the reshaped draw of VAR coefficients.

Labour market

Figure A1 presents the aggregate responses of key labour market variables following a tax cut shock. Specifically, we estimate the benchmark VAR including three labour market indicators over the sub-sample period 1971-2009. The results are broadly consistent with Cloyne (2013): real wages exhibit a significant increase of approximately 2.3% after one year, whereas for the IRF in hours worked, we fail to reject the null hypothesis of no significant response.

While the qualitative patterns align, there are notable differences in the data sources and variable definitions. In our analysis, wages refer to gross weekly earnings from the main job, and hours represent weekly hours worked in the main occupation per household. Both variables are derived from survey data. In contrast, Cloyne (2013) utilises data from the ONS, which reflects total hours worked and earnings per individual.

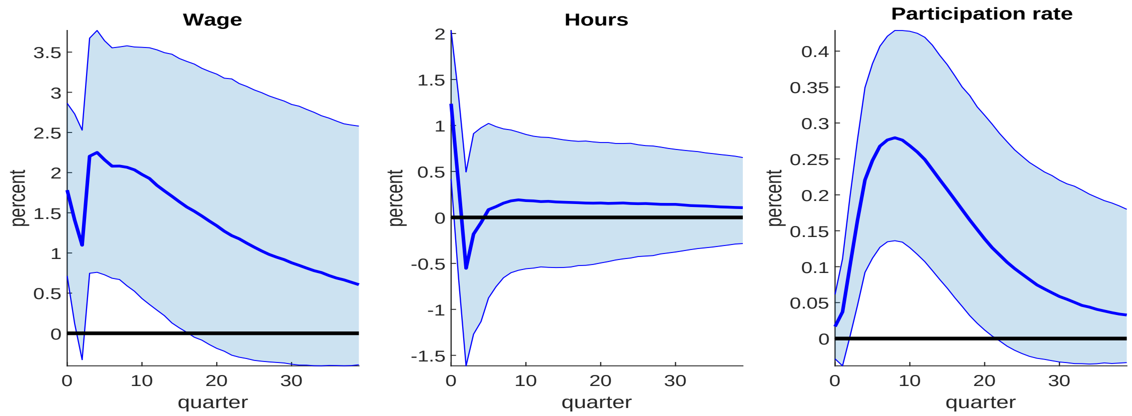

Figure A1: Impulse response functions of aggregate labour market variables to a tax cut of one percent of GDP.

To investigate whether the lack of response in hours worked reflects adjustments at the extensive margin rather than the intensive one, we examine the participation rate. The results indicate a significant increase in the participation rate, suggesting that the observed labour market adjustment is driven primarily by individuals entering the labour force rather than existing workers increasing their hours worked.