The Impact of Aggregate Fluctuations Across the UK Income Distribution

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June 2025

Abstract

In this paper, we examine the response of earnings and employment to fluctuations in aggregate economic activity (GDP) across the income distribution. Using data from the UK's Labour Force Survey, we present evidence that aggregate fluctuations have economically significant but heterogeneous impacts across the income distribution. While the earnings response is broadly similar across the distribution, further decompositions reveal important differences in the channels of transmission. Changes to hours worked and employment better explain the earnings response in the bottom half of the distribution, whereas changes to the hourly wage are more important in the top half. We integrate our empirical results into a HANK model and use it to highlight the importance of these margins of adjustment in determining a broad precautionary savings response of households to a monetary policy shock. We show that this channel is economically significant across the income distribution.

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1 Introduction

Understanding how fluctuations in aggregate economic activity affect individuals and households across the income distribution is essential for evaluating the welfare implications of business cycles and the transmission and effectiveness of macroeconomic policies.

Recent research, notably Guvenen et al. (2017), has begun to examine these distributional dimensions. This paper contributes to that literature by focusing on two areas that remain relatively under explored: first, a decomposition of changes in labour income over the business cycle and income distribution into changes in employment, hours worked, and hourly pay; and second, an application of this decomposition to the UK economy using a Heterogeneous Agent New Keynesian (HANK) model.

Our empirical analysis is based on the UK's Labour Force Survey (LFS), a large survey that underpins the UK's national labour market statistics. A key advantage of the LFS for our purposes is its short panel structure, which tracks individuals for up to five quarters. This allows us to examine how changes in labour income and employment status–conditional on individuals' initial circumstances–are related to aggregate economic fluctuations. As a labour market survey, the LFS also allows a more detailed decomposition of earnings adjustments across both intensive (wage, hours) and extensive (unemployment, inactivity, job switching) margins than has typically been considered in previous work.

We estimate OLS regressions of four-quarter changes in individual labour market outcomes on contemporaneous four-quarter changes in real Gross Domestic Product (GDP), interpreting these coefficients as elasticities with respect to transitory, unanticipated movements in aggregate activity. The main outcome variables that we consider are labour earnings, hours worked, and employment status, including job-to-job transitions. By estimating these regressions separately across initial earnings deciles, we are able to quantify how different parts of the income distribution are affected by business cycle fluctuations—-and through which margins of adjustment.

Our findings indicate that labour earnings respond similarly to GDP fluctuations across much of the income distribution, though we observe excess sensitivity at the bottom decile and relatively muted effects in the upper-middle.[1] Importantly, the nature of adjustment varies systematically across the distribution. For lower-income individuals, earnings fluctuations are driven primarily by changes in hours worked and employment status—-particularly transitions into unemployment. In contrast, for higher-income individuals, adjustments occur mainly through hourly wages. We also find that the probability of job switching is more sensitive to GDP changes in the lower half of the distribution, though this margin plays a relatively minor role in the overall GDP elasticity of earnings.

The fact that those in the bottom half of the income distribution are more likely to move into and out of employment is also true on average, or unconditional on changes in GDP. An important difference that we uncover is the margin of adjustment. In general, most movements from employment to non-employment are due to transitions into inactivity. However, conditional on GDP fluctuations, it is the unemployment margin that dominates, with the response of the inactivity margin estimated to be insignificant.

Our main results focus on general changes in GDP, but using an SVAR we also report results conditional on unanticipated changes in GDP, and changes in GDP identified using monetary policy shock and supply shocks. We conduct these exercises both as an extension to, and validation of, our headline results. The response to monetary policy shocks are of particular interest given the role of monetary policy in stabilising the economy and the existing literature has not explored the response across the income distribution to supply shocks. We find that the responses to these identified shocks are similar to our headline results described above and,

[1] On average, real pay responds by about 0.7 percent to a 1 per cent movement in GDP.

furthermore, do not detect significant differences in GDP betas depending upon the source of the shock.

In additional analysis, we extend our baseline regressions by examining alternative groupings of individuals. When we rank individuals by the average income in their current (or most recent) occupation, we find that the results remain broadly consistent with our main findings. This approach also allows us to incorporate individuals who are initially not employed, enabling us to show that GDP fluctuations significantly affect job-finding probabilities across the income distribution. Further disaggregation by age and sex reveals that younger (16–29) and older (50+) male workers exhibit the highest sensitivity to changes in GDP. For these groups, labour market adjustment occurs predominantly through changes in hours worked and employment status, whereas prime-aged workers (30–49) adjust mainly through hourly wages.

We also find a robust negative relationship between GDP growth and earnings variance across all income deciles. This decline in variance is particularly pronounced in the lower half of the distribution and is primarily driven by changes on the extensive margin. Household-level aggregation yields similar patterns to the individual-level results. Finally, conditioning on recession periods suggests some evidence of asymmetric responses, with larger GDP betas during expansions—consistent with the presence of downward nominal wage rigidity.

Our empirical findings have important implications for fiscal and monetary policymakers seeking to understand the channels, distributional effects, and welfare consequences of policy changes that impact the business cycle. To further explore these implications, we integrate the empirical relationships documented in this paper into an off the shelf HANK model calibrated to UK data. This allows us to quantify a novel broad precautionary savings channel of monetary policy.[2]

We find that this channel can account for approximately 20 percent of the total decline in consumption following a contractionary monetary policy shock. This effect operates primarily through employment risk on the extensive margin and is quantitatively important across the income distribution. Through the lens of the model, our results highlight how heterogeneous labour market adjustments–particularly at the lower end of the distribution—-shape aggregate consumption dynamics and, therefore, the transmission of monetary policy. These findings underscore the importance of incorporating micro-level labour market heterogeneity into macroeconomic models to better understand the full distributional impact of policy interventions.

1.1 Related Literature

This paper fits into a growing literature that seeks to understand the distributional implications for individuals and households of fluctuations in the aggregate business cycle. Guvenen et al. (2017) use a large administrative dataset for the US to document a U-shaped response to fluctuations in GDP across the income distribution, with the incomes of the poorest and richest individuals found to be most exposed to the US business cycle. Other recent studies such as Amberg et al. (2022), Andersen et al. (2022) and Holm et al. (2021) have focused on the distributional implications of monetary policy shocks using administrative data from Sweden, Denmark and Norway respectively.[3] The conclusions from these papers vary, but a common thread is that there is excess sensitivity to business cycle fluctuations induced by monetary policy at the bottom and top of the distribution, with the response of labour income most important at the bottom of the distribution, and changes to capital income more important at

[2]We define this channel as the response of consumption today to the expectation of lower employment income in the future, through lower expected working hours and wages, and higher unemployment risk.

[3]While the findings of these papers can potentially be extrapolated to larger developed economies, contributions such as in this paper are important in establishing the evidence base for this.

the top. Our results for labour income appear consistent with these studies.

This literature has mostly focused on the response of incomes, but some papers such as Broer et al. (2022), Hubert & Savignac (2023), and Hoffmann & Malacrino (2019) also consider extensive margin adjustment. Hoffmann & Malacrino (2019) analyse administrative data from Italy and conclude that employment changes and spells of unemployment contribute to the pro-cyclical skewness of income. As in this paper, Broer et al. (2022) and Hubert & Savignac (2023) find that the extensive margin is key to explaining the excess sensitivity of income to the business cycle at the bottom of the income distribution. We contribute to this aspect of the literature by attempting to provide a more granular decomposition; focusing on adjustment across the income distribution along both the intensive and extensive margins. Within the extensive margin we also decompose adjustment into transitions into inactivity, unemployment, and job switching.

Our paper also contributes to a small UK literature on the incidence of aggregate shocks. Bell et al. (2022) use the UK's Annual Survey of Hours and Earnings (ASHE) - a sample of employees - to study earnings dynamics and inequality over a long sample (1975-2020). They find that the variance of earnings has increased over time and that earnings exhibit pro-cyclical skewness. They also document the exposure of individuals with different characteristics to aggregate shocks, finding that it is declining in age, the size of their employer, skill level and permanent earnings. Relative to their paper, by using the LFS we are able to observe individuals who are not employed, including by studying the extent to which job-loss contributes to the response of labour earnings to aggregate shocks. Our sample also includes employees that are not captured by ASHE, either because they work for a very small firm or because their pay is below the threshold that requires their employer to enter them into the PAYE tax system. Cantore et al. (2023) use US and UK data to study the effect of monetary policy on hours worked and unemployment across the income distribution, including in a pseudo-panel constructed from the LFS. These authors find an initial counter-cyclical response of hours worked at the very bottom of the income distribution conditional on a monetary policy shock, though this effect does not persist to the peak transmission period in the case of the UK. Using a similar pseudo-panel approach Mumtaz & Theophilopoulou (2017) find contractionary contractionary policy has a larger negative effect on low income households. Compared to those studies, we leverage the panel element of the LFS to trace individual outcomes and focus on the broader business cycle as well as monetary policy induced fluctuations.

In addition, we contribute to a wider UK literature on cyclical earnings dynamics and the role of labour market transitions in generating employment fluctuations. Schaefer & Singleton (2019) use the ASHE data to measure the job-level response of wages and hours worked to business cycle fluctuations. They find that firms reduced the real hourly wages of both new hires and job stayers within jobs following the financial crisis, but that only the hours of new hires were affected. Relative to this study, we consider the response of pay to aggregate fluctuations across the income distribution, and are able to examine the role of job-loss. Finally, Elsby et al. (2011), Gomes (2012), Razzu & Singleton (2016) and Singleton (2018) examine the contribution of labour market transitions to cyclical movements in the UK unemployment and inactivity rates. In common with this literature, we find that cyclical variation in the probability of an unemployment transition is the predominant driver of employment fluctuations.

Finally, this paper contributes to the literature that attempts to explain and decompose the monetary transmission channel. Kaplan et al. (2018) highlight the importance of the indirect general equilibrium channels of monetary policy. Auclert et al. (2020) show how expectations matter for empirically consistent transmission of monetary policy in models. We apply our empirical findings to highlight and quantify a precautionary savings of channel of monetary policy in a HANK model that is able to replicate the key relevant empirical evidence. We are therefore able to provide some empirical support for a theoretical channel often cited by policymakers.[4]

The rest of this paper is structured as follows. Section 2 describes the LFS data in more detail and presents key statistics on income, hours and labour market transition rates across the income distribution. Section 3 describes our empirical approach. Section 4 reports our main results, section 5 applies them in a HANK model, and Section 6 concludes.

2 Data and Descriptive Statistics

2.1 Data

This study focuses on data from the UK's Labour Force Survey (LFS) which allows us to track both changes in labour earnings and the labour market status of individuals. The LFS is the largest household survey in the UK and is used to construct headline labour market statistics, such as the unemployment rate, labour force participation rate and hours worked. The survey has been run on a quarterly basis from the spring of 1992 and is designed to achieve a sample of $36,000$ households in each quarter. Individuals from sampled households stay in the survey for five quarters (waves) to enable the analysis of labour market transitions i.e. movements between employment, unemployment and inactivity. Since the spring of 1997, participants have been asked to report their pre-tax labour earnings in both wave 1 and wave 5, enabling analysis of changes in labour income over a 1 year period for employed individuals. Participants are asked to report their pay for the main and, if applicable, 2nd job in which they were employed during a particular reference week. Alongside their current labour market status and recent employment history, they also report the number of hours they work per week in their main job. The LFS measure of labour earnings, while not the official statistic (AWE), tracks the official measure very closely (see Figure A.1.1) and is the preferred source for the pay of the low paid and part time workers (ONS 2015).

We include in our sample all individuals aged 16 and over and focus on the period starting in 1997 (when we can start tracking changes in labour income) and end in 2019 (prior to the pandemic). More detail on the construction of our data is provided in Appendix A.1.

2.1.1 Limitations

LFS respondents who are unemployed or inactive in the labour market do not report any income or receive an income weight. Therefore, the majority of our analysis is restricted to those employed in wave 1 who we then track through to wave 5. Furthermore, self-employed individuals are not asked the income questions in the LFS and so our analysis also abstracts from this section of the labour force. Since the onset of the COVID pandemic in 2020/2021, the LFS has struggled with response rates and uncertainty over the true underlying population has created difficulty in the construction of accurate survey weights. This underscores our decision to end our sample in 2019Q4. Finally, while the LFS is a large nationally representative survey, the sample is smaller than the administrative datasets used in similar analyses in other countries. For this reason we are somewhat constrained in how finely we are able to cut the data and generally conduct our analysis at the income decile level.

2.2 Descriptive Statistics

Our analysis focuses on the response of labour earnings, hours worked and labour market transitions to fluctuations in economic activity across the income distribution. Like Broer

[4]See Greene (2024) for a recent example.

Table 1: Average Characteristics by Income Decile

(a) Income

Period	1	2	3	4	5	6	7	8	9	10
(1996,2003]	44	101	157	204	246	292	346	416	517	856
(2003,2007]	61	133	200	253	303	357	426	511	637	1048
(2007,2011]	69	146	220	279	335	400	476	573	719	1195
(2011,2015]	75	158	234	296	356	426	506	612	768	1273
(2015,2019]	89	185	267	332	394	465	549	662	828	1378

(b) Other Characteristics

Period	1	2	3	4	5	6	7	8	9	10
Avg. Hours	14.4	24.0	32.9	37.0	38.6	39.6	40.4	40.6	40.7	41.9
Part Time (PT)	0.92	0.78	0.36	0.17	0.11	0.08	0.06	0.04	0.03	0.02
PT Student	0.29	0.08	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Female Shr.	0.73	0.76	0.66	0.55	0.48	0.43	0.38	0.35	0.32	0.22
Avg. Age	36.0	39.6	38.0	38.0	38.9	39.5	39.7	40.6	41.9	43.2
Dependents	0.75	0.77	0.58	0.50	0.50	0.51	0.54	0.59	0.66	0.78
Age>60 Shr.	0.13	0.10	0.07	0.06	0.06	0.05	0.05	0.04	0.04	0.04
High Skill Shr.	0.05	0.08	0.09	0.11	0.16	0.23	0.31	0.43	0.59	0.77

Notes: Panel (a) reports nominal pre-tax average weekly earnings by income decile for the specified periods. Panel (b) reports the average of other characteristics by income decile across all periods. Dependents is the average numbers of dependents under 16 within the individuals household. High Skill is based on the ONS classification of occupations (SOC) into four skill levels: we report the share in the highest skill group (level 4).

et al. (2022), we first group households by initial income decile and then take averages over each decile in current and future periods (quarters):

$$y_{g,t+h} = \frac{1}{\sum_i \mathbf{1}_{(i,t)\in g} w_{i,t}} \sum_i \mathbf{1}_{(i,t)\in g} y_{i,t+h} w_{i,t} \tag{1}$$

where i is an individual in the LFS in quarter $t+h, h \in \{0,4\}$, g is an income group (defined at time t), $w_{i,t}$ is the LFS income weight and y is a variable of interest, e.g. labour earnings or an employment indicator.[5] [6]

Average weekly earnings, hours worked and other characteristics are reported by income decile in Table 1. The LFS captures the inequality in UK labour earnings reasonably well, with the top decile reporting incomes 15 times the level of the bottom decile, and the 9th decile reporting incomes at 4.5 times the level of the 2nd decile. However, due to income censoring and a lack of coverage at the very top of the distribution, these ratios are lower than those reported by the UK's tax authority (HMRC), which are closer to 25 and 5.5, respectively.[7] In terms of hours worked, we see that hours are increasing in weekly income, though the differences in hours worked are small in the top half of the distribution, where there are few part time workers. The bottom two deciles are notable for the share of part time workers, older workers and the female share relative to the other income buckets. And within those two deciles, the

[5]In practice, our results are insensitive to the use of income weights as demonstrated in Figure A.1.4. This is due to the fact that these weights are highly correlated with income decile which we condition on in our analysis.

[6]In Broer et al. (2022) households are grouped by permanent income decile based on income history and observables. In the LFS we only observe incomes twice in wave 1 and 4 quarters later in wave 5, and so bin based on regular income reported in wave 1.

[7]HMRC Survey of Personal Incomes.

share of students stands out in the bottom income bucket. Individuals at the bottom and top of the income distribution also tend to live in households with more dependents under the age of 16.

This study is also focused on individual labour market transitions. Figure 1 panel (a) reports average transition rates between quarter t and $t+4$ by income decile in quarter t.[8] We see that average labour market transition rates are close to monotonically decreasing in income. The probability of transitioning out of employment (blue line) is highest at the bottom of the income distribution, and almost four times higher than at the top of the distribution. On average, most (around $\frac{3}{4}$) of these transitions out of employment are into inactivity (orange line), with the remainder explained by transitions into unemployment (cyan line). Those at the bottom of the income distribution are also more likely to switch jobs (purple line) than those at the top.

The propensity for more frequent labour market transitions at the bottom of the distribution is further reflected in higher real pay growth variance for these groups. Panel (b) of Figure 1 plots average pay growth variance by initial income decile which takes the form of an incomplete U shape, with variance highest at the bottom and lowest in the upper-middle deciles 7 and 8. By comparing to the orange dashed line we can see that the differences in pay growth variance are nearly completely explained by extensive margin transitions, with the variance for those that remain employed in both periods nearly flat across the income distribution.

Finally, while average transition rates vary across the distribution it's notable that even in the middle and upper deciles, transitions between jobs or into non-employment are quite common. This underscores the value of being able to follow individuals in a panel as opposed to conducting analysis on a pseudo-panel, where this margin is either omitted or imputed. In terms of movements along the income distribution between waves, in further analysis (see Appendix A.1.3) we find that the large majority of individuals either remain in the same income decile or move into adjacent deciles.

3 Empirical Framework

Our empirical approach follows other similar work, such as Guvenen et al. (2017) or Broer et al. (2022), by running simple regressions of changes in different outcome variables on changes in aggregate economic conditions (GDP) by income decile. We refer to the elasticity, β_g, resulting from these regression as a GDP beta. The outcomes we focus on are: real labour income growth (log difference); hours growth (log difference); the linear probability of a transition to unemployment or inactivity; and the linear probability of changing jobs.[9] Our main GDP beta regressions are specified as follows:

$$y_{g,t+4} - y_{g,t} = \alpha_g + \beta_g \Delta GDP_{t+4} + \epsilon_{g,t} \tag{2}$$

where β_g is an unconditional GDP elasticity for GDP growth over the same four quarter period. This elasticity can be interpreted as a variance weighted average of elasticities with respect to a slow moving growth trend and the elasticity to transitory business-cycle frequency fluctuations.

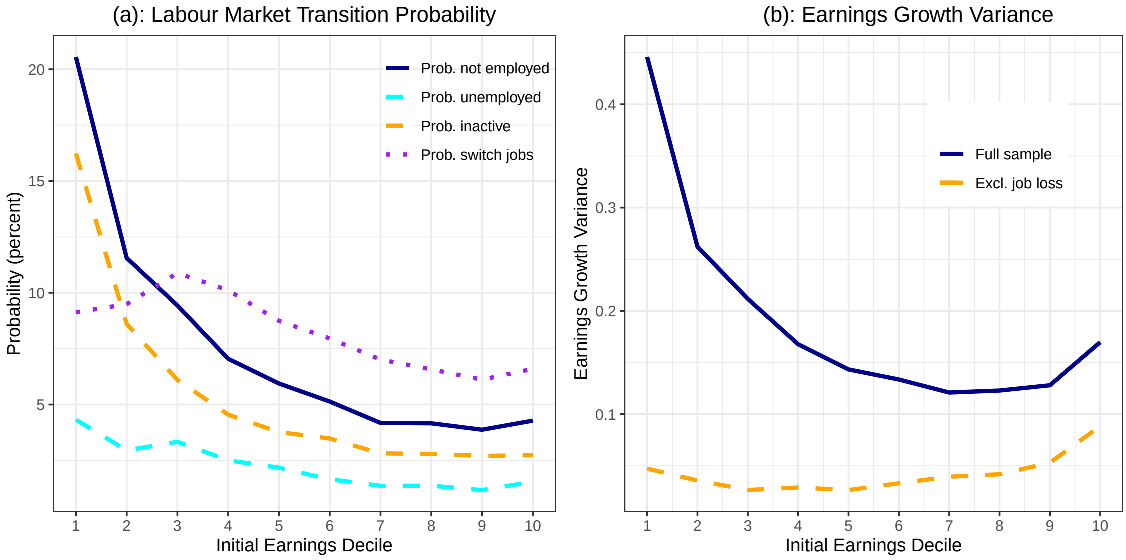
To see this, consider the case in which the data generating process for individual wage growth is as follows:

$$dy_{i,t} = dL_{i,t} + dz_{i,t} + \gamma_1 dg_t + \gamma_2 da_t \tag{3}$$

[8]Note that unlike our main results, these averages are not conditional on changes in GDP and so represent a mix of steady-state and business cycle induced transitions.

[9]We use real GDP growth and real income growth in our regressions, where the latter is nominal earnings deflated using the GDP deflator. More detail on the construction of our data is provided in Appendix A.1.

Figure 1: Unconditional Moments



Notes: Panel (a) shows average labour market transition probabilities between t and $t+4$. The dark blue line shows the probability of leaving employment; the cyan line shows the probability of becoming unemployed; the orange line shows the probability of becoming inactive; and the purple line shows the probability of changing employer. Panel (b) plots the variance of earnings growth between period t and $t+4$ across our sample period. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

where the change in GDP is $dgdp_t = dg_t + da_t$ is composed of a slow moving growth trend dg and faster moving business cycle component da. Individual pay growth is also determined by returns to age and experience, dL, and by idiosyncratic shocks dz. If we were to then estimate the regression:

$$dy_{i,t} = \alpha + \beta dgdp_t + \epsilon_{i,t} \tag{4}$$

we would obtain the following coefficient estimates for α and β:

$$\alpha = E[dL] + E[dz] + \frac{E[dgdp]}{Var(dgdp)}(\gamma_1 - \gamma_2)E[da^2] \tag{5}$$

$$\beta = \frac{Var(dg)}{Var(dgdp)}\gamma_1 + \frac{Var(da)}{Var(dgdp)}\gamma_2 \tag{6}$$

where we have assumed $E[da] = 0$ and $E[dadg] = 0$, i.e. transitory aggregate shocks average zero and are uncorrelated with long-run trend growth. From Equation (6), we can see the unconditional GDP beta (β) is a variance share weighted average of the elasticities with respect to the trend and the business cycle growth components of GDP. If most of the variance of UK GDP growth is determined by shorter run business cycle movements, as suggested by Melolinna & Tóth (2016) when estimating a GDP filter under similar assumptions, then this unconditional elasticity will largely reflect the elasticity with respect to those transitory business cycle frequency movements in GDP. From Equation (5), we can also see that the constant α_g largely picks up the income group specific trends, such as mean reversion of individual idiosyncratic transitory shocks and growth related to the life-cycle earnings profile.

Based on the insights above and in addition to our main approach, we also estimate GDP betas after isolating more specific transitory business cycle frequency movements (da) in GDP. We do so because it may be the case that the responses to transitory shocks are sufficiently different to unexpected changes in trend growth i.e. $\gamma_1 \neq \gamma_2$. The response to explicitly identified shocks such as monetary policy shocks is also of interest in and of itself and a focus of the related literature (e.g. Amberg et al. (2022)). To do so, we estimate Equation (2) via two stage least squares, instrumenting for changes in GDP with different identification strategies. Our identification strategies rely upon a six variable SVAR outlined in Appendix B that combines IV and sign restrictions. We instrument for GDP changes using lagged monetary policy shocks, supply shocks and the one year head forecast errors from the VAR.[10] Further details on our identifcation strategy and first stage IV results are reported in Table B.1.1.

4 Results

In this section, we report the results that we obtain from applying the empirical approach outlined in the previous section using UK data. We first present unconditional GDP beta estimates before discussing the estimates that we obtain after using the instrumental variables strategy outlined above to isolate transitory, business cycle fluctuations in GDP growth. Finally, we present GDP beta estimates that we obtain from a number of additional exercises.

4.1 GDP Betas

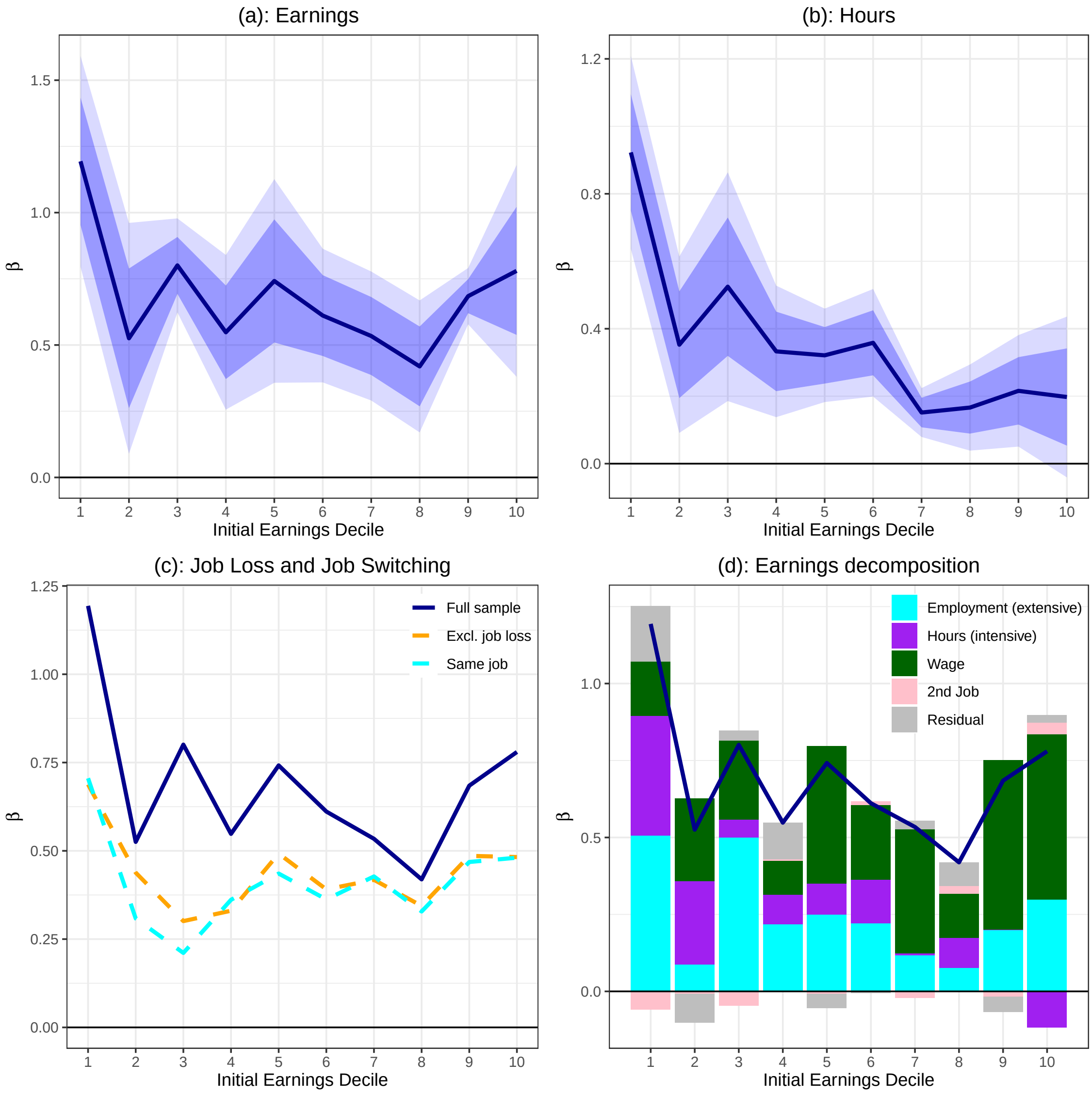
Our main estimates of β_g from Equation (2) for real earnings and hours are displayed in panels (a) and (b) of Figure 2. The impact of GDP movements on real earnings (panel (a)) is economically and statistically significant across the income distribution and on average a movement in GDP of 1 per cent is associated with a change in real labour earnings of around 0.7 per cent.[11] The overall picture is of a reasonably similar GDP beta estimate for earnings as we move across the distribution from the lowest to the highest income groups, although there is some evidence of excess sensitivity at the bottom of the distribution. In particular, the GDP beta estimate for the first earnings decile is significantly different from the estimates for deciles 6 to 8 at the 5 per cent level. Panel (b) of Figure 2 focuses on the response of hours worked to a 1 per cent change in GDP. We find a notably downward sloping profile for the GDP beta, with an estimated GDP beta for hours similar to that of earnings in the bottom half of the distribution but smaller in the top half of the distribution.

The different shape of the GDP beta profiles for earnings and hours displayed in panels (a) and (b) of Figure 2 suggests that the margin of adjustment to fluctuations in aggregate conditions varies across the income distribution, with hours playing the dominant role in the bottom half of the distribution whereas changes in hourly earnings would seem to be more important at the top. In panels (c) and (d) of Figure 2, we therefore present some direct evidence on these differences. Panel (c) compares the point estimate from panel (a) in dark blue to the results from two sub-samples. The orange dashed line shows the point estimate only for those individuals that remain employed in period $t+4$. The estimated GDP betas for those that remain employed are uniformly below the whole sample estimates, and by a large margin for some income deciles in the bottom half of the distribution. This points to an important role for the extensive margin in accounting for the sensitivity of earnings to GDP fluctuations across the income distribution, particularly at the bottom. The dashed cyan line in panel (c) further restricts the sample to those that stay in the same job. It is not materially different

[10] We use high frequency shocks identified in 30 minute windows around MPC instruments and focus on movements in the three month short sterling futures contract expiring 3-6 months after the announcement (see Cesa-Bianchi et al. (2020) for more details). To instrument for changes in GDP we use accumulated shocks from one and two years prior in line with the significance of the transmission dynamics captured in the VAR illustrated in Figure B.1.2.

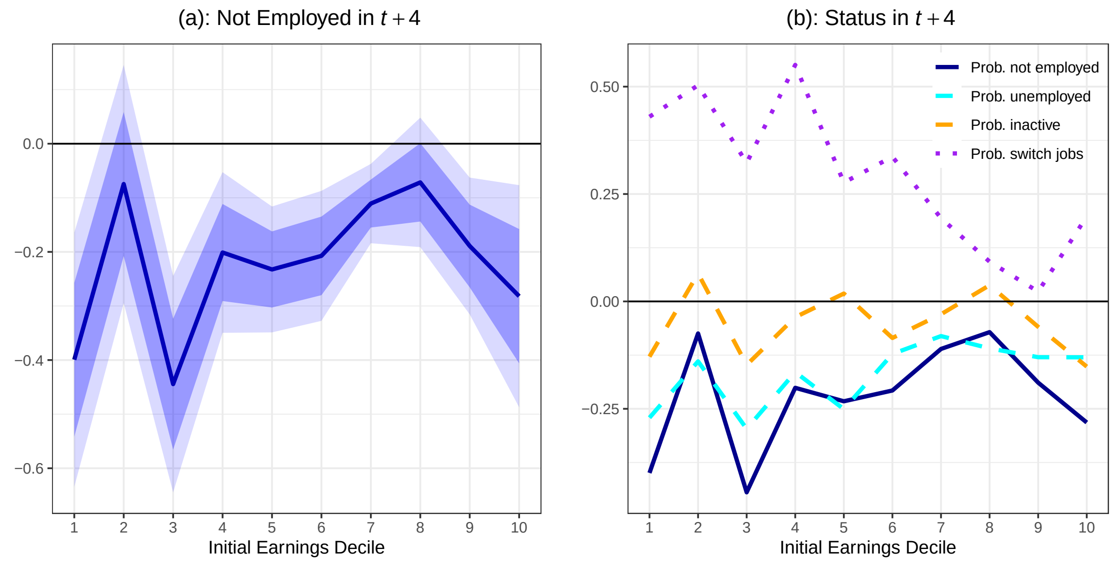
[11] Bell et al. (2022) estimate 0.38 per cent using a longer sample of UK earnings data from ASHE.

Figure 2: GDP Betas for Earnings and Hours



Notes: Panels (a) and (b) plot the coefficients β_g from Equation (2) for changes in labour income and hours worked (in main job), respectively. The darker (lighter) shaded area represents the 68% (90%) confidence interval calculated using HAC standard errors. Panel (c) plots the coefficients β_g from Equation (2) for different samples: the blue line plots the coefficients for the full sample, as in panel (a); the orange dashed line plots the coefficients for those individuals that remain employed in $t + 4$; and the cyan line plots the coefficients for those individuals that remain with the same employer in $t + 4$. Panel (d) decomposes the earnings response reported in panel (a) into the responses of: the extensive margin (aqua bar), intensive margin (purple bar), the hourly wage (green bar) and earnings in second jobs (pink bar). Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4 in each panel.

Figure 3: GDP Betas for Labour Market Transition Probabilities



Notes: Panel (a) plots the coefficients β_g from Equation (2), with the probability of non-employment in $t+4$ as the dependent variable. The darker (lighter) shaded area represents the 68% (90%) confidence intervals calculated using HAC standard errors. Panel (b) plots the coefficients β_g from Equation (2) with different dependent variables: the blue line plots the coefficients using the probability of non-employment as the dependent variable, as in panel (a); the cyan line plots the coefficients using the probability of unemployment as the dependent variable; the orange line plots the coefficients using the probability of inactivity as the dependent variable; and the purple line plots the coefficients using the probability of having a new employer as the dependent variable. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

from the orange dashed line, suggesting that job switching is not a significant determinant of the overall GDP beta.

In a final step, panel (d) presents a decomposition of the earnings response reported in panel (a) into the contributions of adjustment on the extensive and intensive margins, changes in the hourly wage and in earnings from additional jobs.[12] The decomposition confirms the differences in the margins of adjustment to GDP fluctuations that were suggested by the previous panels. In particular, the greater importance of adjustment in hours worked due to extensive and intensive margin adjustment at the bottom of the earnings distribution and, conversely, a greater role for changes in the hourly wage in the upper half of the distribution.

The results displayed in Figure 2 have highlighted an important role for the extensive margin in explaining the sensitivity of earnings to aggregate fluctuations. In Figure 3, we therefore further investigate this margin of adjustment by using labour market transitions as the dependent variable in Equation (2). Panel (a) plots the GDP beta for the linear probability of moving from employment in period t to non-employment in period $t+4$. A 1 per cent increase (decrease) in GDP is associated with around a 0.2 percentage point reduction (increase) in the probability of moving to non-employment on average across the distribution. With the exception of the first and second deciles, the point estimate of the GDP beta for non-employment is upwards sloping towards the upper middle portion of the income distribution where it is not significantly different from zero.

In panel (b) of Figure 3, we decompose the probability of moving out of employment by

[12] See Appendix B for more detail. The LFS data only allow a decomposition of earnings in main jobs. The residual in the decomposition reflects that the product of the arithmetic weighted mean of the individual components is not exactly equal to the arithmetic weighted mean of the change in earnings (hours x hourly pay).

showing the point estimates for the linear probability of becoming unemployed (cyan line) and the probability of becoming inactive in the labour market. We also plot the probability of switching jobs (purple line). The close proximity of the unemployment line to the overall blue non-employment line suggests that it is the unemployment margin that drives the response of extensive margin transitions to GDP fluctuations. Movements to inactivity are statistically insignificant. This latter result contrasts with the steady-state–or average–transition probabilities shown in Figure 1, where the majority of movements into non-employment are explained by movements into inactivity. However, it is in line with previous findings that cyclical variation in the probability of an unemployment transition is the predominant driver of employment fluctuations in the UK (Elsby et al. 2011, Gomes 2012, Razzu & Singleton 2016, Singleton 2018). This underscores the importance of conditioning on GDP, as otherwise a policymaker could erroneously infer the margin through which their policies are likely to transmit. Finally, in Figure 3 we note that the GDP betas for job switching are downward sloping across the income distribution, more so than for the unconditional transition rate (Figure 1).

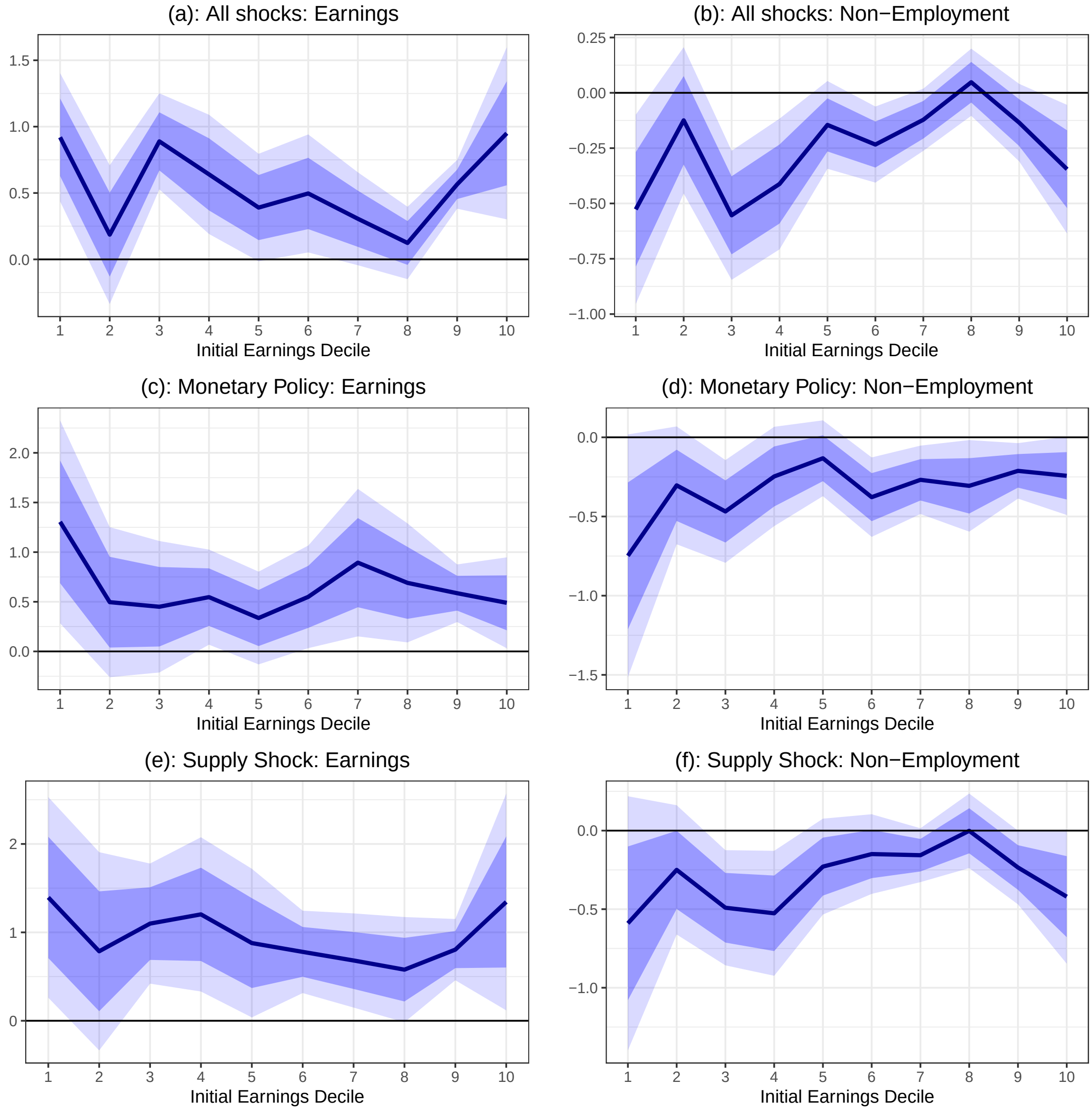
Focusing on the bottom two deciles, it's perhaps surprising relative to the patterns across the rest of the distribution to see reversals in the point estimates between deciles at the bottom of the distribution, as we do in panel (a) of Figures 2 and 3. From Table 1, we know that the bottom two deciles are mostly part-time workers and when we remove those that are initially part-time employed from our sample, the results are smoother and more downward sloping without significant reversals across the distribution (see Figure C.2.1). However, one of the advantages of our approach using the LFS is that we capture these low paid and part-time employees where they are often missed in other analyses.[13] It's likely that workers in this part of the distribution may exhibit different and more heterogeneous labour supply characteristics. For example, aside from being part-time employed, we have shown that those in the first decile are more likely to be a student or above 60 whereas those in the second decile are part of households with higher numbers of dependants but are otherwise more similar to the other deciles. It's possible that part-time students and older workers may, for example, be more demand determined, taking hours as they come. Whereas those in the second decile may exhibit more insensitive labour supply as welfare program incentives (e.g. low income support) and caring responsibilities may dictate their labour supply to a greater degree than other parts of the distribution (Beffy et al. 2019).

4.2 Transitory Shocks

As discussed in Section 3, the GDP beta estimates reported in the previous sub-section reflect a variance-weighted average of trend growth (dg) and transitory business cycle movements in GDP around trend (da). In this sub-section, we attempt to isolate those more transitory, business cycle frequency fluctuations by using GDP forecast errors, monetary policy shocks and identified supply shocks as first stage instruments for GDP growth, as outlined in Table B.1.1. The key results are shown in Figure 4. The first row shows the results for the forecast errors approach where we instrument GDP changes with the error in the one year ahead forecast ('All shocks') from the VAR. The pattern and magnitude of the estimates are quite similar to that of our main results. We find significant effects across the income distribution and the GDP beta for earnings (panel (a)) is again reasonably similar across the distribution. However, when taking this approach, we find less evidence of excess sensitivity at the bottom of the distribution and a more muted, even insignificant response in the upper middle. We again find that the extensive margin again plays an important role in determining this earnings response (panel

[13] By deliberately excluding part-time workers from the sample or by using data that fails to capture them for administrative reasons. For example, the ASHE dataset misses employees from non-VAT registered firms and employees below the national insurance earnings threshold.

Figure 4: GDP Betas for Transitory Shocks



Notes: Panel (a) and panel (b) plot the coefficients β_g from Equation (2) under an instrumental variable approach using GDP forecast errors from the VAR discussed in Appendix B as an instrument for GDP growth. Panel (c) and (d) follow the same procedure but use accumulated high frequency monetary policy shocks as the instrument. Panels (e) and (f) use temporary supply shocks identified using the VAR. The darker (lighter) shaded area represents the 68% (90%) confidence intervals calculated using HAC standard errors. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

(b)), with the point estimates similar to our main result (Figure 3).

The second row of Figure 4 shows the results for monetary policy shocks, i.e. movements in earnings and employment probabilities conditional on a 1 percent movement in GDP that is due to past unanticipated interest rate changes. Earnings are again significantly impacted across the income distribution. While still elevated at the bottom of the income distribution, the point estimates of the GDP beta for earnings in panel (c) are flatter than in Figure 2, though the confidence intervals are larger. The pattern for the linear probability of non-employment (panel (d)) is more similar to our other results, with heightened sensitivity in the bottom half of the distribution. Finally, the bottom row instruments GDP with supply shocks identified by combining sign restrictions and IV restrictions in the same VAR (see section B).[14] We again see significant, but fairly flat GDP betas across the distribution. The extensive margin channel is again strongest in the bottom half. Taken together with additional results reported in Appendix C.1, and as hypothesised in Section 3, the overall conclusions that we draw from the instrumental variable approach are similar to those from the unconditional approach. Furthermore, we don't detect noteworthy differences between shock identification strategies.

4.3 Other Exercises

4.3.1 Alternative Groupings

In this section, we discuss GDP beta estimates that are obtained from alternative groupings of individuals. The first alternative grouping is considered in order to address one of the limitations of our main approach. The short-panel structure of the UK LFS means that in order to group individuals into income deciles, we are restricted to only considering those that are initially employed, as discussed in Section 2. That stands in contrast to other work, such as Guvenen et al. (2017) and Broer et al. (2022), which uses administrative data to construct a measure of permanent income for all individuals with some income history, and can therefore consider the earnings responses of both employed and non-employed individuals.

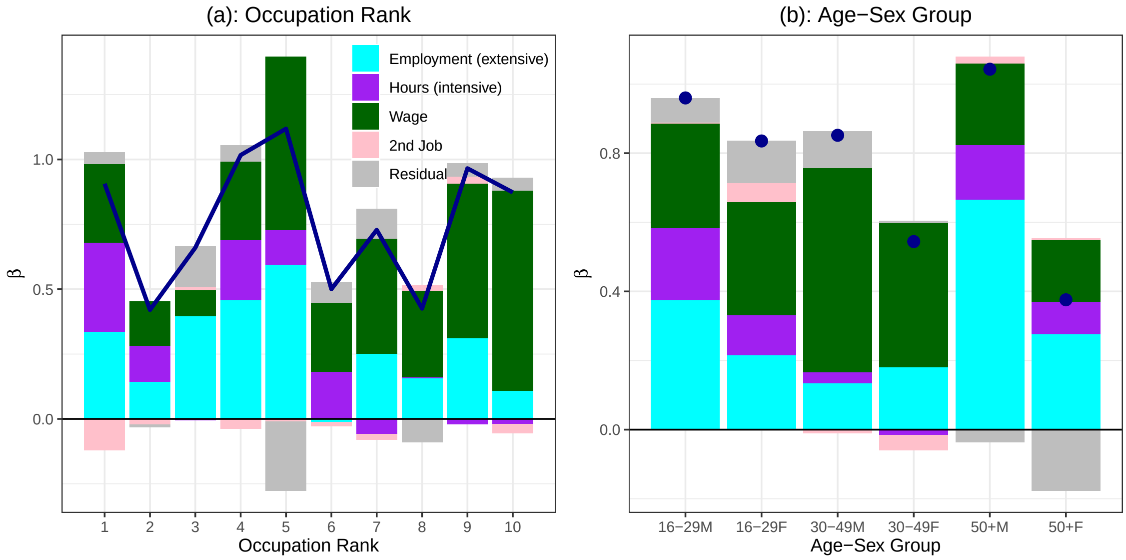
In order to investigate whether our results are robust to the inclusion of initially non-employed individuals–within the limitations given by our use of the LFS data–we consider GDP beta estimates that are obtained after grouping individuals based on a proxy measure of their permanent labour income. In particular, we group individuals based on their current or–for those initially not employed–most recent occupation, and rank these occupations by average hourly income across all periods.[15]

The main results of this exercise are displayed in panel (a) of Figure 5. The panel shows a decomposition of the GDP beta estimates for the ranked occupation groups into the contributions of extensive and intensive margin adjustments, changes in the hourly wage and in income from additional jobs, as in panel (d) of Figure 2. We find that the results from this exercise are broadly coherent with our main results. In particular, we again find reasonably similar GDP beta estimates across the distribution, as we move from the lowest paid occupations to the highest. Importantly, we also confirm that, although the GDP beta estimates are similar, the margin of adjustment is different for those in the bottom and top halves of the (permanent) income distribution. Namely, the earnings response in the bottom half of the distribution is

[14] We also identify generic demand shock using sign restrictions and an energy price supply shock. The results are reported in Figure C.1.2. The oil shock turns out to be a weak instrument for GDP and did not generate statistically significant betas. The demand shock appears to have captured the volatility in the top row of Figure 4 giving an unclear picture for overall earnings betas but a similar story as the other shocks on the extensive margin.

[15] We group individuals using the three UK Standard Occupational Classifications (SOC) that were in place during the period which we study: SOC1990, SOC2000 and SOC2010. In each case, we use the 3-digit classification of around 90 occupations. To rank these occupations, we calculate the average hourly pay for each occupation for the period in which the classification is in place.

Figure 5: Decomposition of GDP Beta for Earnings for Alternative Groupings



Notes: Panels (a) and (b) plot decompositions of the GDP beta for labour earnings, following the approach described for panel (d) in Figure 2. In panel (a), individuals are ranked according to the average income of their occupation, or previous occupation for those not employed, in t. In panel (b), individuals are grouped by their reported age and sex in t. The sample period is 1997Q2-2019Q4.

predominantly explained by the response of hours worked–due to both extensive and intensive margin adjustments–while the response in the top half is predominantly explained by changes to the hourly wage.

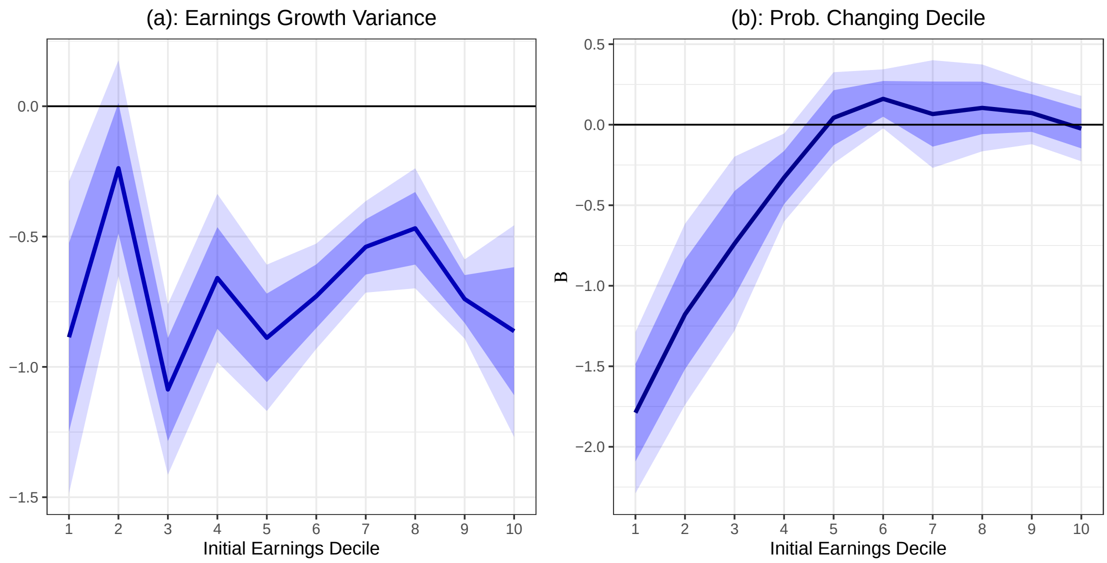
Further investigation of the responses of employment entry and exit probabilities to GDP fluctuations is discussed in Appendix C, and displayed in Figure C.3.1. The response of the employment exit probability is broadly upward sloping across the distribution, again providing support to our main results. The response of the entry probability–a margin that we are unable to consider when ranking individuals by initial income–is found to be reasonably similar across the distribution. In both cases, it is the probability of transitioning to and from unemployment that is found to be most responsive to GDP fluctuations.[16]

The second alternative grouping that we consider is based on an individual's age and sex in the first period of observation. When grouping individuals by age and sex, we are also able to include individuals that are not employed in the initial period, in common with the occupation grouping approach discussed above, but in contrast with our main approach. The GDP beta estimates for males and females aged 16-29, 30-49 and 50+ are displayed in panel (b) of Figure 5, again decomposed following the approach outlined for panel (a). We again find that the overall GDP beta for earnings is relatively similar across groups. The earnings response is explained to a greater degree by changes in hours worked–due to adjustment along the extensive and intensive margins–in the younger and older age groups, while the response for those aged 30-49 is predominantly explained by changes to the hourly wage. This finding is line with previous work that has found a higher labour supply elasticity for younger and older individuals.[17] Further results for the responses of the employment exit and entry probabilities is provided in Appendix C.

[16]The GDP betas for the unemployment to employment transition probability are imprecisely estimated, due to the small sample of individuals that are initially unemployed. Given this, in calibrating the HANK model for the exercise described in Section 5, we choose to use an average response, as documented in Appendix C.

[17]For example see French & Jones (2012) or Jaimovich et al. (2013).

Figure 6: GDP Betas for Earnings Variance



Notes: Panel (a) plots the coefficients β_g from Equation (2) with within initial income decile pay variance $Var(dy_{t+4})$ on the LHS. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. Panel (b) plots the GDP beta for the probability of changing income decile or changing labour market status (i.e. going to decile 0). Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4. HAC standard errors reported.

4.3.2 Income Variance

The change in the variance of income growth across the distribution is a further object of interest and a theoretically important determinant of household consumption. For example, Storesletten et al. (2001) estimate that the variance of persistent shocks to disposable household income more than doubles in US recessions. Figure 6 plots the GDP betas for the change in the variance of pay growth by income decile for initially employed people as well as the GDP beta for the probability of changing income decile.[18] We see that GDP betas for pay variance are negative across the distribution i.e. positive fluctuations in GDP reduce income variance. The reduction in variance, while statically significant is however relatively small when compared to the average variances (unconditional on GDP changes) reported in most income deciles in Figure 1. Panel (b) plots the probability of changing income deciles or becoming not employed i.e. going to a decile zero. Here there is a pronounced difference between the bottom and top half again suggesting different drivers of the GDP betas in different parts of the distribution with the fall in variance at the bottom more driven by a fall in probability of becoming unemployed.

4.3.3 Additional Exercises

We conduct two additional exercises which we summarise in this section and illustrate in Appendix C. As a household survey, the LFS interviews each member of sampled households which enables us to aggregate our dataset to the household level. It is possible that GDP betas for earnings could look different when grouping and sorting households instead of individuals.[19] For example, an individual's labour supply decision may reflect the labour market status of other members of their household (Lundberg 1985). The results of this exercise are displayed in Figure C.5.1. For most income deciles, we find that the GDP beta estimates are not sig-

[18] Here the LHS variable in our regression is pay growth variance within each group between wave 1 and wave 5.

[19] The majority of the related literature has also conducted its analysis at the individual level.

nificantly different from the individual-level results reported in Section 4.1. One difference is a greater sensitivity in the first decile. Taken together, these results do not suggest that within-household insurance cushions the response of incomes to GDP fluctuations.

We also consider whether controlling for (discounting) periods of negative growth–and in particular the Great Recession–affects our GDP beta estimates. We do this by including indicators of negative growth between periods t and $t+4$ as an interaction term with GDP growth in Equation (2). The results of this exercise are displayed in Figure C.6.1. The estimates are again similar to our main results, particularly for the extensive margin transitions. We do find some statistically significant differences in the estimated GDP betas for earnings for some deciles, with estimated GDP betas higher on average in response to positive GDP movements, consistent with findings of downward real wage rigidity (Grigsby et al. 2021).

5 Model Application

In this section, we demonstrate how some of the results from Section 4 can be applied to the calibration of a HANK model. To do this, we take the suggested baseline HANK model for fiscal and monetary policy analysis of Auclert et al. (2024), and alter the agents income process to incorporate sensitivity to the business cycle in line with the estimates in Section 4.

In brief, the model is a one account HANK model with sticky wages, passive fiscal policy and a central bank that follows a Taylor rule. Agents cannot borrow but can save in a liquid investment account (a) and are subject to an uncertain labour productivity process (z_i). Their period budget constraint is as follows:

$$\begin{aligned} a_{i,t+1} + c_{i,t} &= (1 + r_t)a_{i,t} + z_i h_t w_t (1 - \tau_t) + T_G \\ a_{i,t+1} &\geq 0 \end{aligned}$$

where c is consumption, r is the real return on the liquid account, h is average hours worked, w is their real wage, τ the tax rate and T_G is a lump sum transfer.

We calibrate the model to key UK macroeconomic averages, marginal propensities to consume (iMPCs) and the impulse responses from our SVAR (Figure B.1.2). Details on the model structure and calibration are reported in Section D. Overall, the model captures key statistics on the marginal propensity to consume, average wealth levels, average labour market transition rates and the dynamic aggregate response to a monetary policy shock. We solve the model in the sequence space following the methods of Auclert et al. (2021).

5.1 Incorporating the Betas

Most HANK models in the existing literature generate an endogenous income and wealth distribution through modelling agents as being exposed to idiosyncratic productivity shocks. Often, an agent's idiosyncratic ability to produce labour services is modelled as an AR1 process–or a mix of AR1 processes–which is calibrated to reproduce certain moments related to the income distribution e.g. total variance of cross-sectional income. These processes tend to abstract from specifically modelling a non-employment state, though implicitly the variance in the income processes tends to embed such transitions. They are also not typically a function of the business cycle.

To incorporate our GDP beta estimates, we model agent's labour productivity ($z_{i,t}$) in each period as being defined by two states: (1) a state describing their productivity when employed

Table 2: GDP Betas and Transition Probabilities in the Model

Income decile	1	2	3	4	5	6	7	8	9	10
Steady State EU (%)	3.7	2.6	2.9	2.2	2.0	1.6	1.4	1.3	1.1	1.5
Steady State UE (%)	41.1	50.7	57.4	57.4	54.5	66.0	63.4	63.7	67.1	62.4
β_g	0.09	-0.12	-0.34	0.02	-0.07	-0.11	0.35	0.11	0.10	-0.03
$\beta_{g,EU}$	-0.37	-0.37	-0.48	-0.27	-0.25	-0.13	-0.09	-0.12	-0.13	-0.08

Notes: Steady state transition probabilities calculated based on sample average by income decile over 1997-2019. These are annual (4 qtr) transition probabilities and betas which are converted to quarterly values in the model jointly using a numeric solver. β_g is the excluding job loss Beta for the monetary policy case, de-meaned to account for fluctuations in average hours worked and the real wage in the model. $\beta_{g,EU}$ is the Beta for the employment to unemployment probability under the monetary policy identification.

and (2) a state defining their employment status. Their final income also depends on the business cycle. This is formalised below:

$$
\begin{aligned}
z_{i,t} =& (z_{i,t,p} + \beta_g(z_{i,t,p})\hat{y}_t)E_{i,t} \\
z_{i,t,p} =& \rho_z z_{i,t-1,p} + \epsilon_{i,t,p}, \qquad \epsilon_{i,t,p} \sim N(0, \sigma_z^2) \\
E_{i,t} =& \begin{cases} 1, 1 - P(z_{i,t,p}, E_{i,t-1}) - \beta_{g,E}(z_{i,t,p}, E_{i,t-1})\hat{y}_t \\ 0, P(z_{i,t,p}, E_{i,t-1}) + \beta_{g,E}(z_{i,t,p}, E_{i,t-1})\hat{y}_t \end{cases}
\end{aligned}
$$

with persistent labour productivity modelled as an AR1 process. The probability of being employed ($E = 1$) depends on the agent's current productivity, previous employment status, and the output gap. We have therefore incorporated our GDP betas in reduced form, as a multiplier on the output gap.

In practice, we discretise the AR1 labour productivity process into 10 points, akin to the 10 income deciles groups of Section 4.[20] Each point along the income distribution then has an employed/unemployed state giving a total of 20 discrete points for z_i. We calibrate the income process to be persistent ($\rho_z = 0.97$) and such that it recreates the average intensive margin cross-sectional variance of 4 quarter changes in labour income ($\sigma_z = 0.1$).[21] For the employment state, the steady state employment to unemployment probabilities and unemployment to employment probabilities, are taken as the sample averages by income decile in the data. The GDP betas are taken directly from our results for the monetary policy case.[22] See Table 2 for the precise values that enter the model. Here we have reported four quarter transition probabilities consistent with our beta estimates. In the model we use a numeric solver to guess and jointly solve for the equivalent quarterly values that would produce these annual values by income decile. We also estimate an average unemployment to employment beta ($\beta_{g,UE} = 2.18$) and include that in the model (see Table C.4.2). Here we do not vary the beta by income decile as we were not able to establish reliable evidence of it varying over the distribution systematically (Figure C.3.1) and for the fact our methodology for estimating U to E ratios differs in sorting household by occupation not actual income. We focus on unemployment transitions because in steady state agents will transition into and out of inactivity for a variety of non-pecuniary reasons, and for the fact we have shown that unemployment transitions are the significant margin of adjustment related to the business cycle.

[20] Using the Rouwenhorst method.

[21] Approximately the average of the yellow dashed line in Figure 1 panel (b), a variance of about 4.2 percent

[22] This is for consistency with our model calibration, where the model dynamics are calibrated to match the impulse responses to a monetary policy shock.

5.2 GDP Betas and Precautionary Saving

Incorporating GDP betas in the manner described above creates potential for greater amplification in the model by making income inequality and income risk more counter-cyclical (see discussion by Bilbiie (2024)). It creates the potential for a strong precautionary savings channel that may be absent from normal modelling strategies that abstract from job loss or the covariance of job loss probabilities with the business cycle.

This is illustrated in Figure 7. In panel (a), we plot the aggregate consumption response in red to an unanticipated monetary policy shock. The dark blue bars (GDP beta channel) break out the partial equilibrium effect on consumption of the change in relative income across the income distribution and the change in probability of job loss/finding.[23] The effect is large, accounting for around one third of the fall in consumption at the peak point of the total fall. Panel (b) further breaks the beta channels into direct income (Inc) and precautionary savings channels (PS). Direct income channels refer to the direct effect on income of the GDP betas on consumption in the current period. Precautionary savings as we define it, is the effect on consumption in the current period from anticipated changes in income and employment risk in the future.[24] This is a broad definition of precautionary savings that includes all changes in consumption in anticipation of future changes in income and not just changes related to income risk[25]. We further break these channels into extensive and intensive margin channels. This reveals that the GDP beta channel is dominated by the extensive margin and in large part due to precautionary savings, with agents reducing consumption when faced with an increase in job loss risk. The intensive margin effect is negligible, due to the fact that intensive margin GDP betas are fairly flat across the income distribution and that they were demeaned so as not to double count movement of average hours and wages in the model.

Panel (c) of Figure 7 looks at the consumption response across the income distribution at the peak fall in aggregate consumption. This shows consumption falling most at the bottom of the income distribution and least at the top, with those at the top of the income distribution tending to be wealthier and most able to optimally smooth through the shock. We decompose the consumption fall by decile into precautionary saving channels (blue and grey) and other channels (red). Here we also include precautionary saving related to lower expected average hours and wages (PS-other). This is a channel that would be present without modelling GDP betas. Panel (c) highlights that the precautionary saving channel is prevalent across the income distribution, accounting for around 20 per cent of the fall in consumption by income decile. The precautionary savings channel associated with total average hours is smaller and highlights the potential importance of modelling the extensive margin in the context of precautionary savings. Specifically, the small but non-negligible change in the risk of a prolonged unemployment spell across the income distribution. This is reinforced in panel (d), which compares the baseline model to a model with no GDP betas or extensive margin.[26] In the alternative model (no Ext.), we replace the income process with a simple AR1 income process that delivers the same cross-sectional variance and variance in 4 quarter change in income as the baseline model: a standard HANK calibration strategy. For the sake of comparison, we consider the household consumption response in both models under the same baseline paths for the aggregate variables that affect consumption (hours, wages, taxes, interest rate).[27] This also implies the same path

[23] See appendix D.4 for more details on how to create these decompositions.

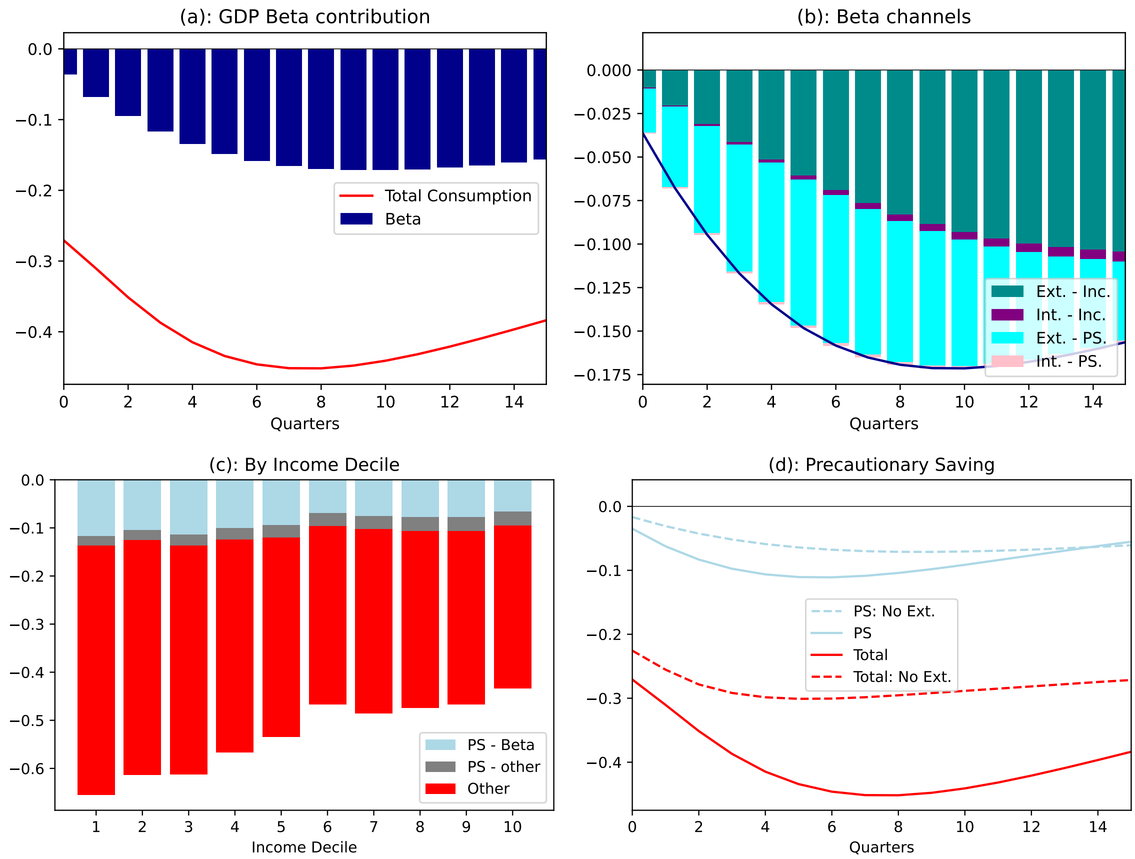
[24] For example moving to unemployment reduces income to zero in that period which will decrease consumption now and in the future.

[25] These are difficult to disentangle in the linear sequence space framework. For example a fall in the expected path of hours work reduces the central expectation of income but it also increases risk by making any idiosyncratic future changes in productivity more costly.

[26] This is a model that has the exact same calibration strategy i.e. same externally calibrated parameters, total wealth and MPC targets.

[27] We also account for unemployment, which changes in the baseline model but not the alternative.

Figure 7: GDP Beta Contribution to Dynamic Consumption Response



Notes: Panels isolate the effect of the GDP betas and precautionary saving on the consumption response to a monetary policy shock (see appendix Fig D.3.1). In panel (a), the red line is the total aggregate response and the blue bars are the partial equilibrium effect of the relative movements in income and employment across the distribution. Panel (b) further decomposes these blue bars into direct income (Inc) and precautionary savings (PS) channels for the intensive and extensive margin. Panel (c) plots the average effect by income decile at the peak of the aggregate fall and decomposes it into precautionary saving and other channels. Panel (d) compares the consumption response in the baseline model to an otherwise identically calibrated model with no GDP betas or extensive margin, under the same path of other aggregate variables relevant to household consumption.

for GDP. We see in panel (d) that the path of aggregate consumption is much lower in the alternatively calibrated model. This is initially explained by a smaller precautionary savings channel. Subsequently, the differences are driven by endogenous persistence from higher iMPCs beyond the first period in the baseline model (see Figure D.2.1 and D.2.2) that follows from more persistent risk of hitting the borrowing constraint through persistent elevated employment risk.

In summary, incorporating empirically estimated GDP betas into a HANK framework introduces an important amplification mechanism by making income risk and inequality more counter-cyclical. This generates a quantitatively significant precautionary savings channel–particularly through the extensive margin–that standard models omitting job loss risk may fail to capture. Our decompositions show that GDP betas account for roughly one-third of the peak fall in consumption, with precautionary savings alone contributing around 20 percent. These effects are strongest at the bottom of the income distribution and are driven not only by direct income losses but also by heightened employment risk, which raises the likelihood of future borrowing constraints. Comparing to a model with a standard AR(1) income process and no GDP betas, we find a markedly weaker and less persistent consumption response, all else equal, suggesting the importance of accounting for heterogeneous labour market risk—especially via the extensive margin—in capturing the full transmission of macroeconomic shocks.

6 Conclusion

Using data from the UK's Labour Force Survey, this paper provides new empirical evidence on the impact of GDP fluctuations on real earnings and labour market outcomes across the income distribution. We document that aggregate fluctuations have statistically and economically significant heterogeneous impacts across the income distribution. We find movements in labour earnings are relatively similar across the distribution with some evidence of greater sensitivity at the very bottom of the income distribution. When decomposing changes in real earnings, we find that changes in earnings in the bottom half of the distribution are explained more through changes to hours worked and transitions into unemployment. In contrast, adjustments in the top half of the distribution are better explained by changes to hourly wages. These findings also hold on average across identification strategies e.g. conditioning specifically on monetary policy shocks or supply shocks.

We incorporate these empirical estimates into the calibration of a Heterogeneous Agent New Keynesian (HANK) model for the UK, showing that accounting for these heterogeneous impacts and employment risk generates amplification through a precautionary savings channel that is quantitatively important across the income distribution.

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A Data

In this section, we provide more detail on the LFS variables and other data that we use in our analysis.

A.1 LFS data

As discussed in Section 3, we construct the following outcome variables using the LFS data:

- **Sample**

  We include in our sample those aged 16 and over from LFS cross sectional data waves 1997Q2 to 2019Q4.

- **Labour income**

  The main outcome that we consider is the annual change in real weekly labour income: nominal weekly labour income deflated using the GDP deflator (see next section). We use the sum of gross weekly pay in the main job (*GRSSWK*) and, if applicable, second job (*GRSSWK2*).

  In the decomposition that we report, we also consider the change in real hourly pay in an individual's main job. This is constructed by dividing nominal weekly pay in an individual's main job (as described above) by the hours that the individual usually works in that job (described below).

  We group individuals reporting income in wave 1 into initial income deciles in each LFS wave. If individuals report that the amount that they were paid for their main job was different to usual, we use the usual pay that they report (*USUGPAY*) converted to a weekly amount using the period covered by that pay (*GRSPRD*).

  For those employed in wave 1, we remove those earning less than £37.5 in real terms, approximately half the real rate of job seekers allowance over the sample period. We also windsorize calculated real income growth, removing the top 1 per cent as suspected outliers.

- **Hours worked**

  The LFS only records information on the usual hours that individuals work in their main job. Depending on an individual's circumstances, we construct this using information from the following variables: total usual hours worked excluding lunch breaks (*TOTUS1*); usual hours worked excluding overtime (*USUHR*); and usual hours of paid overtime (*POTHR*).

- **Labour market transitions**

  Labour market transitions are constructed using the labour force status (*ILODEFR*) reported by individuals in wave 1 and wave 5 of the survey.

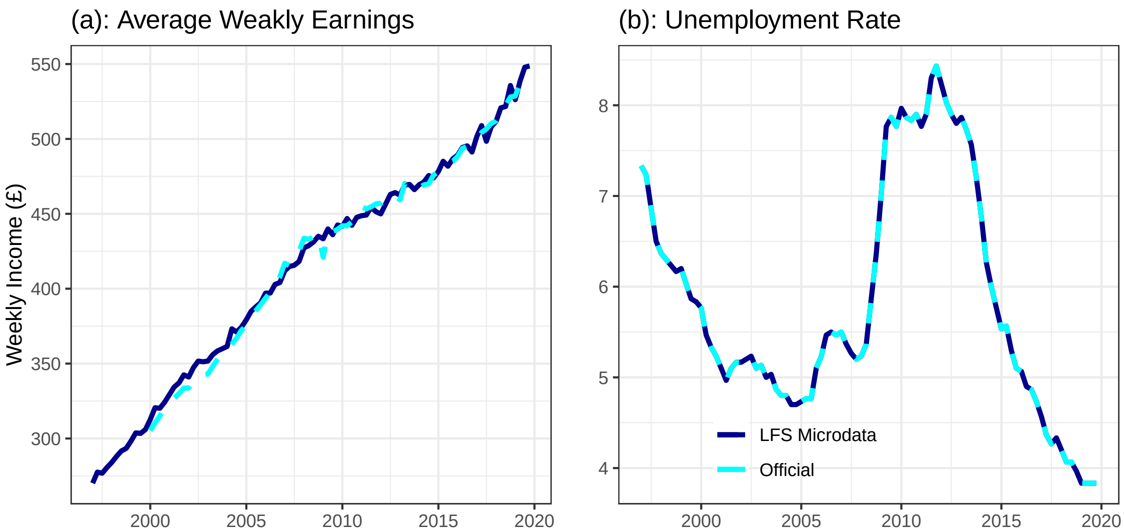
- **Job switching**

  Individuals who have changed employer are identified using information on their tenure (*EMPLEN*).

- **Income Weights**

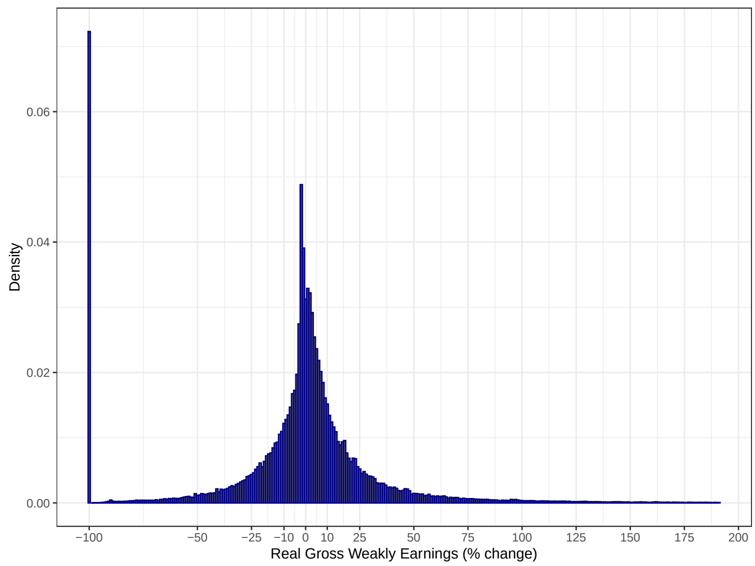
  Our analysis is focused on income changes and so we use the cross sectional data wave 1 income weights to weight individuals when aggregating the data as in equation 1. As some employed in wave 1 will become not employed in wave 5 we use the income weights from wave 1 in the wave 1 and wave 5 aggregations. Our results are not sensitive to the use of weights, however, as indicated in Figure A.1.4.

Figure A.1.1: LFS Microdata Compared to Official Series.



Notes: Figure compares aggregate series constructed using the LFS microdata used in this study to the headline figures reported by ONS. The LFS data aggregates are calculated using the provided survey weights, and then seasonally adjusted using the X13-ARIMA procedure. The official AWE measure from ONS is available from January 2000.

Figure A.1.2: Earnings Growth Distribution

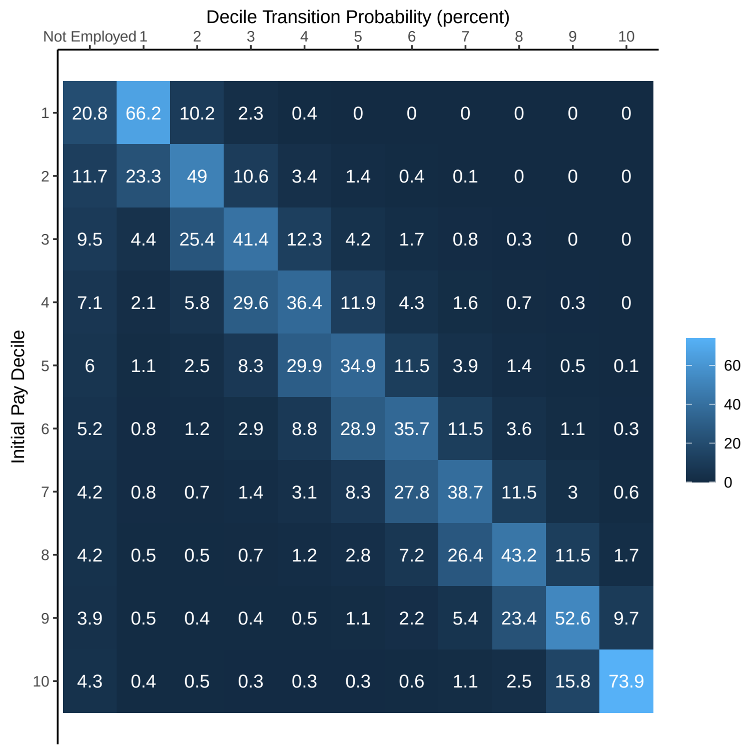


Notes: Figure reports the distribution of growth in real gross weakly earnings for indivdiuals accross the entire sample 1997-2019.

A.2 Other data

- **GDP**

Figure A.1.3: Earnings Decile Transition Matrix



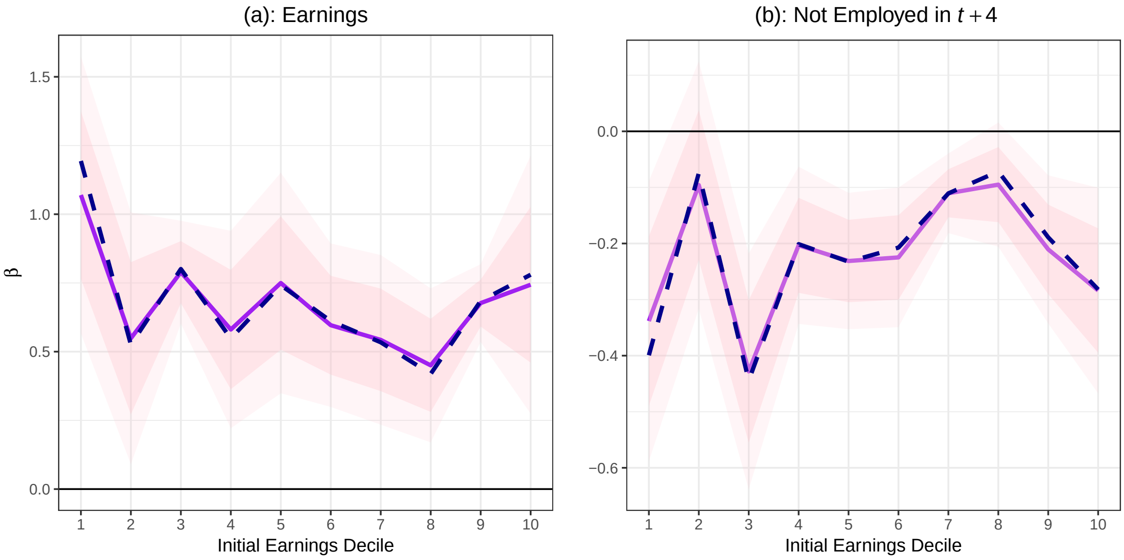
Notes: Figure reports the average probability over our sample of transitioning to each pay decile or non-employment over 4 quarters conditional on an individual's pay decile in period t.

Latest ONS estimate of real GDP ($ABMI$), the annual log change of which is used as an explanatory variable in Equation (2).

- **GDP deflator**

  Latest ONS estimate of the GDP deflator ($YBGB$), used to delate labour income constructed using the LFS data.

Figure A.1.4: Impact of Person Income Weights on GDP Betas



Notes: Figure reports the GDP betas for earnings and labour market transition probabilities from Figure 2 panel (a) and Figure 3 panel (a) constructed without using ONS person income weights. The blue dashed lines are the corresponding results using the income weights, as reported in Section 4.

B Empirical Framework

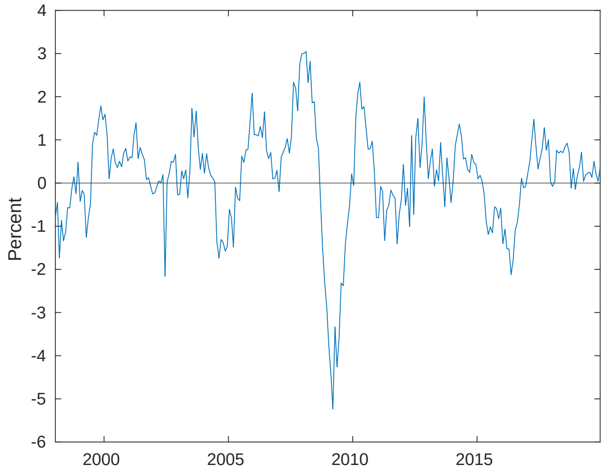
B.1 SVAR

The SVAR described below supports our analysis by allowing us to identify transitory structural shocks, and by providing a framework for forecasting GDP from which we can extract one year ahead forecast errors. The VAR is composed of six variables:

1. 1 year Rate: Monthly average of 12 month spot rate on UK government debt (Bank of England);
2. Exchange Rate: UK effective exchange rate index (Bank of England). A geometric weighted average of selected bilateral exchange rates;
3. FTSE: FTSE All share index (Refinitiv);
4. Spreads: Difference between ICE Bank Of America Sterling Corporate Index and 5 year UK government debt yield;
5. GDP: Monthly Gross Domestic Product (ONS);
6. Core CPI: Consumer price index excluding energy, food, alcohol and tobacco (ONS). Seasonally adjusted.

The VAR is estimated using monthly observations from 1996 to 2019 and 12 lags with figure B.1.1 plotting the 1 year ahead forecast errors.

Figure B.1.1: One Year Ahead Forecast Errors



Notes: Figure plots the forecast errors as the actual realisations of log GDP minus the forecasts from the VAR 12 months prior.

B.1.1 Transitory structural shocks

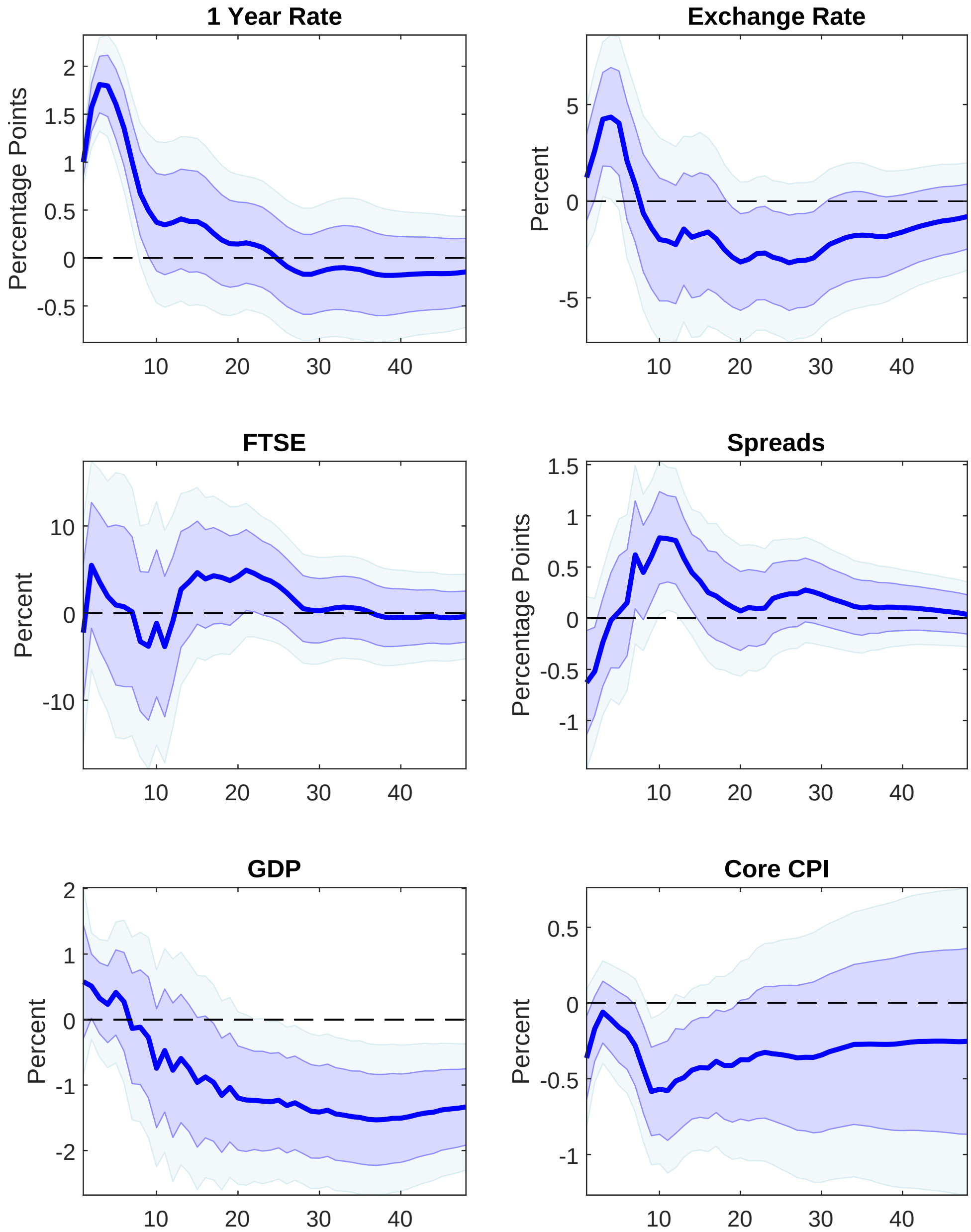
The effect of monetary policy is identified using the external (proxy) instruments approach (Stock & Watson 2018). The instrument for monetary policy shocks is taken as the change in the price of sterling futures contracts in the 30 minutes around UK Monetary Policy Committee announcements. Specifically, we take the difference in the sterling futures contract that settles in the quarter following the announcement based on the 3-Month London Interbank Offered Rate (LIBOR). Following Bauer & Swanson (2023), we further clean our instrument $\hat{z}_t$ for information effects by orthogonalising with respect to information x_{t-} available in the 30 days priors to each announcement window:

$$\hat{z}_t = \beta x_{t-} + z_t \tag{B.1.1}$$

where x_{t-} includes the change in the FTSE all share in the 30 days prior to the annoucnment, the change in the effective exchange rate, the change in the 1 year government borrowing rate, change in corporate spreads and the change in GDP in the month prior to the announcement.

Figure B.1.2 shows the effect of our identified monetary policy shocks in the monthly SVAR. We can see the effects of the monetary policy shock on GDP take some time to build and only become significant at the 68 per cent confidence interval beyond 18 months and 90 per cent level beyond 24 months.

Figure B.1.2: Impulse Response to a 1 per cent Monetary Policy Innovation



Notes: Figure shows impulse responses to a 1 per cent monetary policy shock. Standard errors are derived using a moving block bootstrap (Jentsch & Lunsford 2022) with centered 68 and 90 per cent confidence intervals reported in blue.

We identify two further structural shocks using sign restrictions. We do so by repeating the following procedure until we have collected 1000 models that accord with our sign restrictions and the IV identification:

1. Draw a set of VAR residuals u_t from bootstrapped residuals (1 of 1000 different estimates).
2. Calculate the covariance matrix from the residuals $\Sigma = u_t u_t'$.
3. Calculate the Cholesky decomposition $\Sigma = B_c B_c'$ where B_c is a lower triangular matrix.
4. Solve for 5 rotation (Givens) matrices R_G such that the first column of $B_{c,iv} = B_c \prod_{i=1}^{5} R_{G,i}$ accords with the monetary policy shock identified by on residuals u_t.
5. Draw a random orthonormal (5x5) matrix R that rotates the latter 5 columns of $B_{c,iv}$.

6. Compute impulse responses for the selected structural matrix $B_{c,iv}R$ and check sign restrictions.

7. If sign restrictions satisfied save the model.

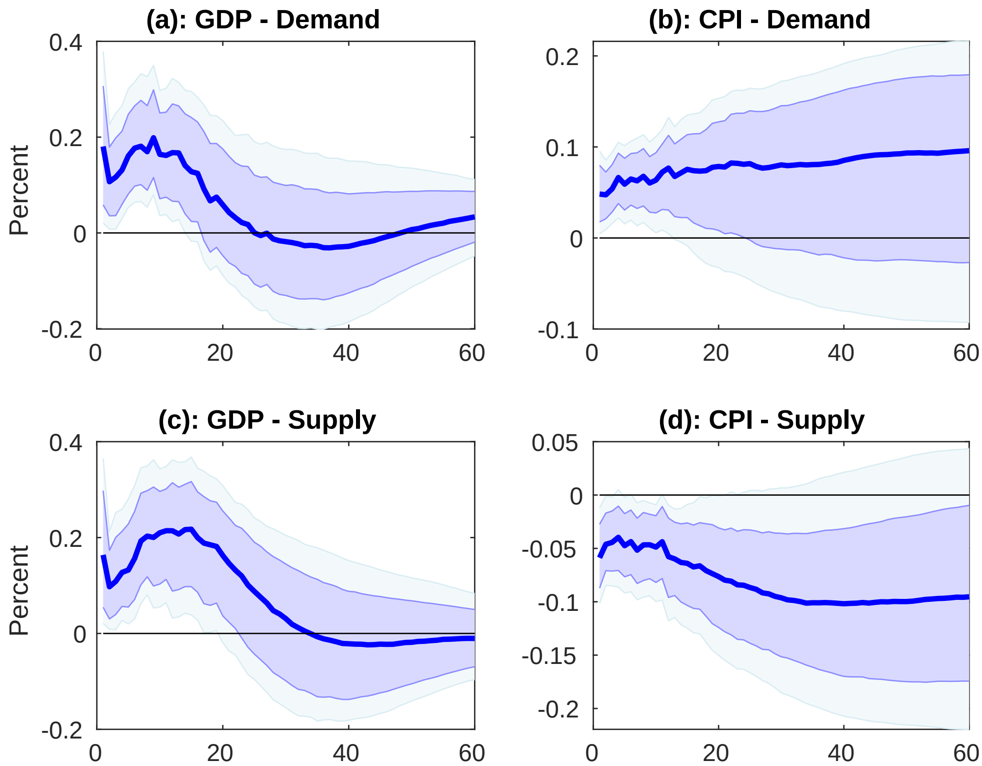
We repeat the above procedure until we have saved 1000 models. We look for models that contain two further shocks:

1. Supply shock: Identified as causing a contemporaneous increase in GDP and stock market price, and decrease in the CPI index. We also require the effect on GDP to persist for 12 months i.e. the IRF for GDP is greater than zero for 12 months.

2. Demand shock: Identified as causing a contemporaneous increase in GDP, stock market price, interest rate and CPI index. We also require the effect on GDP to persist for 12 months i.e. the IRF for GDP is greater than zero for 12 months.

The impulse response to the identified supply and demand shocks are shown in Figure B.1.3.

Figure B.1.3: Supply and Demand Shocks



Notes: Figure plots the impulse responses to identified supply and demand shocks. The shaded regions represent the 68 percent and 90 percent acceptance regions.

B.1.2 Instrumental Variables

We assess the impact of identified structural shocks by estimating Equation (2) via two stage least squares. Table B.1.1 reports the first stage regression results for five different approaches.

In the first approach we sum monetary policy shocks from one and two years prior to wave 1. We use lagged shocks for the monetary policy approach based on the significance of the transmission dynamics captured in Figure B.1.2. Shocks between wave 1 and wave 4 were not strong enough instruments for GDP. In the second approach we use the VAR to forecast GDP

Table B.1.1: First Stage Regression on GDP

Instrument:	Monetary Policy	All Shocks	Supply	Demand	Oil
$z_{1,t}$	-6.32*	1.04**	4.26*	4.12*	-0.27
	(3.60)	(0.32)	(2.30)	(2.74)	(0.18)
$z_{2,t}$	-4.06				
	(2.689)				
constant	0.020***	0.018***	0.021***	0.021***	0.021***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)
F-stat	12.85	58.68	14.58	14.08	7.0
R^2	0.22	0.41	0.13	0.13	0.07

Notes: Table shows results from first stage regression $\Delta GDP_{t+4} = \delta z_t + \epsilon_t$. HAC standard errors reported: *p<0.1; **p<0.05; ***p<0.01.

growth over the next year and take the residual of that forecast (Figure B.1.1) and actual GDP growth as our instrument. The purpose of this instrument is to isolate the unexpected or surprise component of GDP growth between waves which is a product of all 6 shocks. The third and fourth approach use the identified supply and demand shocks. Here we use the SVAR for each of the 1000 models and take the average over all models as our instrumental variable. We take the sum of shocks between wave 1 and wave 4 as our final instrument. Finally we take the sum of oil supply shocks between wave 1 and wave 4 from the published series based on the method of Känzig (2021) as an energy supply shock instrument. The results from the first stage regression is outlined in Table B.1.1 where we can see that the approaches are able to explain a significant amount of the variation in GDP growth, with the possible exception of the Oil price shock.

B.2 Decomposition of GDP beta for earnings

In addition to individual GDP estimates for labour earnings, we also present decompositions of this response into the contributions of adjustment on the extensive (employment) and intensive (hours) margins, changes in the hourly wage and in earnings from additional jobs. For example, in panel (d) of Figure 2.

The individual contributions are constructed as follows:

- **Extensive margin**: The overall earnings response minus the earnings response for those individuals that are employed in both periods.
- **Intensive margin**: The response of hours worked in their main job for those individuals that remain employed in both periods.
- **Hourly wage**: The response of hourly pay in their main job for those individuals that remain employed in both periods.
- **Additional earnings**: The response of earnings in additional jobs for those individuals that remain employed in both periods.

The small residual that appears in these decompositions is due to the product of the arithmetic weighted mean of the individual components not being exactly equal to the arithmetic weighted mean of the change in earnings (hours x hourly pay).

C Additional Results

C.1 Additional Results with Transitory Shocks

C.1.1 Further decompositions

In this subsection we further decompose the results in Figure 4, following the approach that we followed in constructing Figures 2 panel (d). Across identification strategies, the extensive margin and hours worked tend to explain more of the GDP Beta in the bottom half of the distribution.

C.1.2 Other transitory shocks

Figure C.1.2 reports the results for the demand shock and oil price shock IV approach. Both approaches do not indicate significant effects or differences across income deciles for overall earnings. In the case of the oil shock, that is partially explained by the fact the oil supply shock series was a weak instrument for 4 quarter GDP growth. We do see some differences in terms of the employment response to the demand shock with those in the lower half of the income distribution most affected.

C.2 Part Time Employees

Most of our results have exhibited some volatility and reversals within the first 3 deciles. And as shown in Table 1, there are a large number of part-time employees in these deciles. In this sub-section, in order to better understand the role that part-time employees may be playing in exaggerating or distorting our conclusions, we remove part-time employees from the initial period of our sample (period t) and re-estimate our key exercises.[28] The main results without part time employees are are shown in Figure C.2.1. Outside of the first three deciles, the responses are the same as there are very few part time employees in these deciles. The reversal between deciles two and three when using this sample is negligible. The estimated GDP beta for the first decile is now significantly larger, indicating that full time workers are more sensitive to fluctuations than part-time workers at the bottom of the income distribution.

C.3 Additional Results with Alternative Groupings

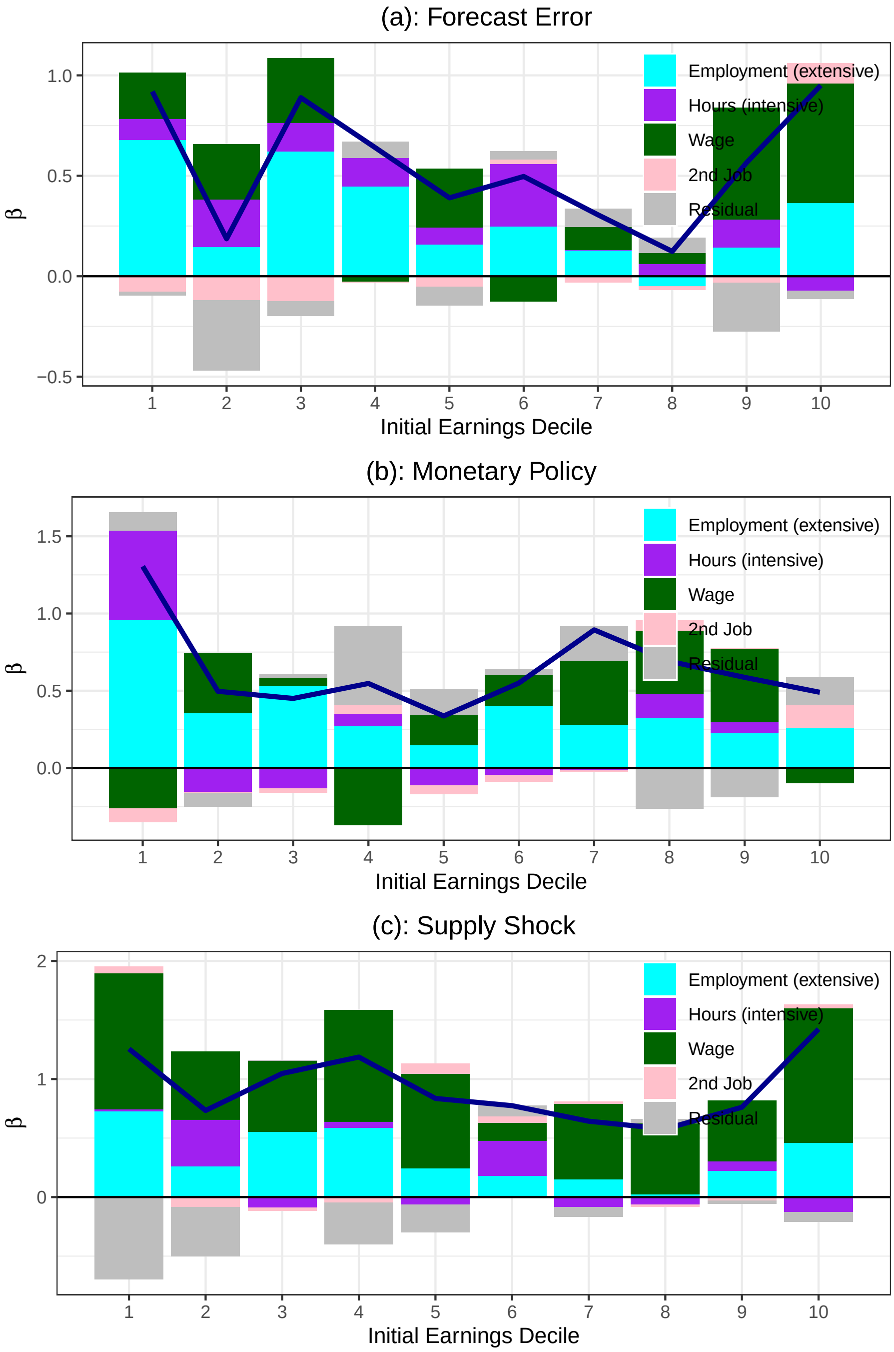
As discussed in Section 4, in addition to the grouping of individuals by income decile based on their earnings in the first period of observation, we also consider two alternative approaches.

The first aims to address one of the limitations of our main empirical strategy compared to previous studies. In particular, due to the short-panel structure of the UK LFS, in order to group individuals into income deciles, we are restricted to only considering only those that are employed in the first period of observation. To examine whether our results are robust to the inclusion of individuals that are initially not employed, we consider GDP beta estimates that are obtained after grouping individuals based on a proxy measure of their permanent labour income. In particular, we group individuals based on their current or—for those initially not employed—most recent occupation, and rank these occupations by average hourly income across all periods.

The second alternative grouping that we consider is based on an individual's age and sex in the first period of observation. When grouping individuals by age and sex, we are also able to include individuals that are not employed in the initial period, in common with the occupation grouping approach discussed above, but in contrast with our main approach.

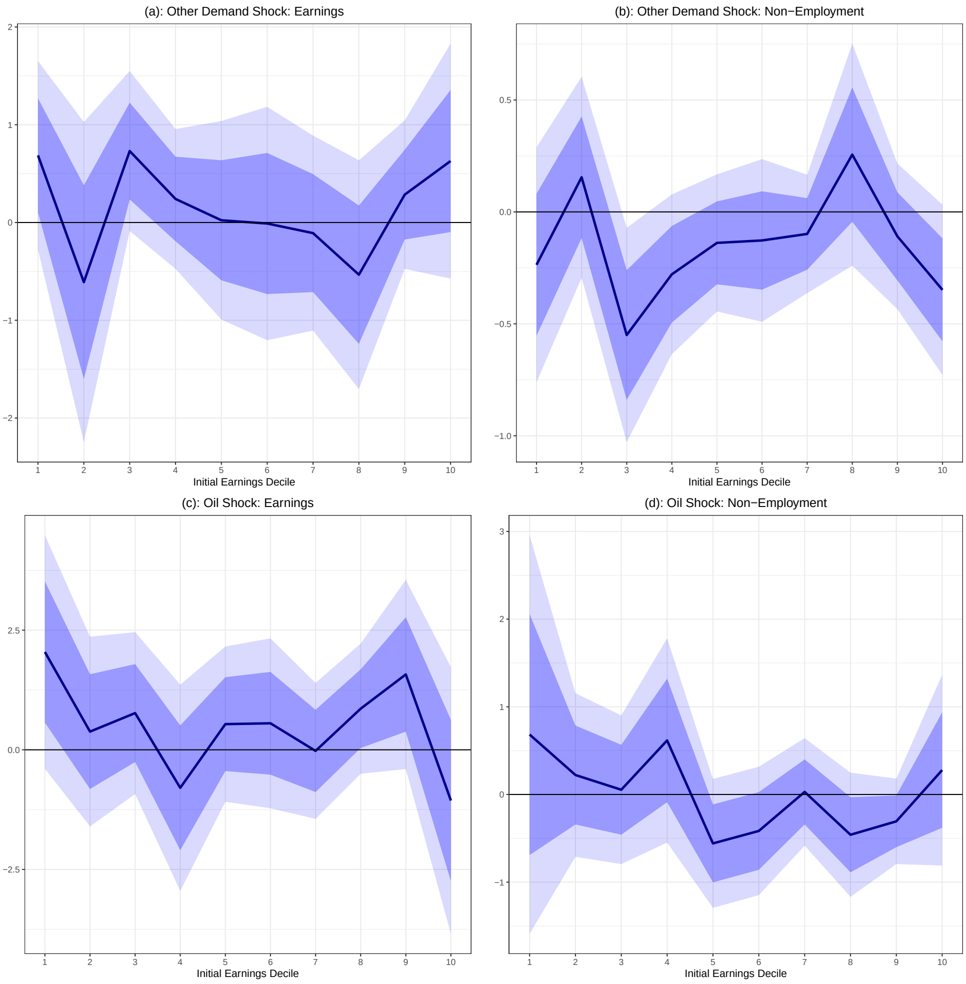
[28] Note that employees transitioning to part-time work are retained in the sample.

Figure C.1.1: Decomposition of GDP Betas: Transitory Shocks



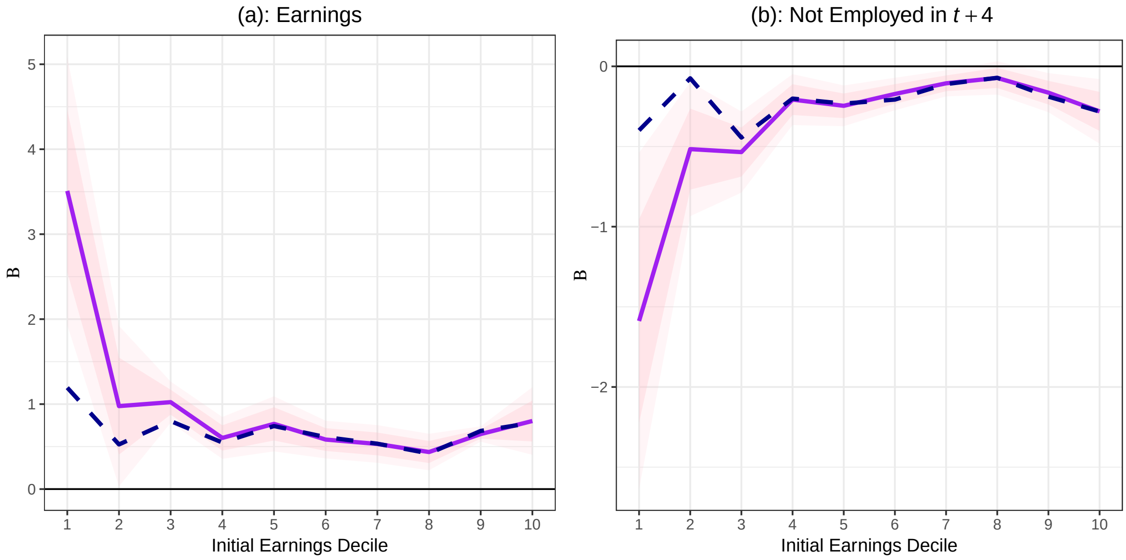
Notes: See notes for Figure 2. Figure decomposes GDP betas under different identification strategies into specific intensive and extensive margins.

Figure C.1.2: Transitory Shocks



Notes: Panel (a) and panel (b) plot the coefficients β_g from Equation (2) under an instrumental variable approach using GDP the other demand shock (Figure B.1.3) as an instrumental variable for GDP growth. Panel (c) and (d) follow the same procedure but use accumulated oil supply shocks. The darker (lighter) shaded area represents the 68% (90%) confidence intervals calculated using HAC standard errors. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

Figure C.2.1: GDP Betas (excluding part-time workers in t)



Notes: The purple line plots the coefficients β_g from Equation (2) but excluding part time workers in the initial period. Income deciles are not recomputed. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. Individuals are sorted into deciles in each quarter based on usual individual earnings in t. The blue dashed line repeats the estimate from Figure 2 panel (a). The sample period is 1997Q2-2019Q4. HAC standard errors reported.

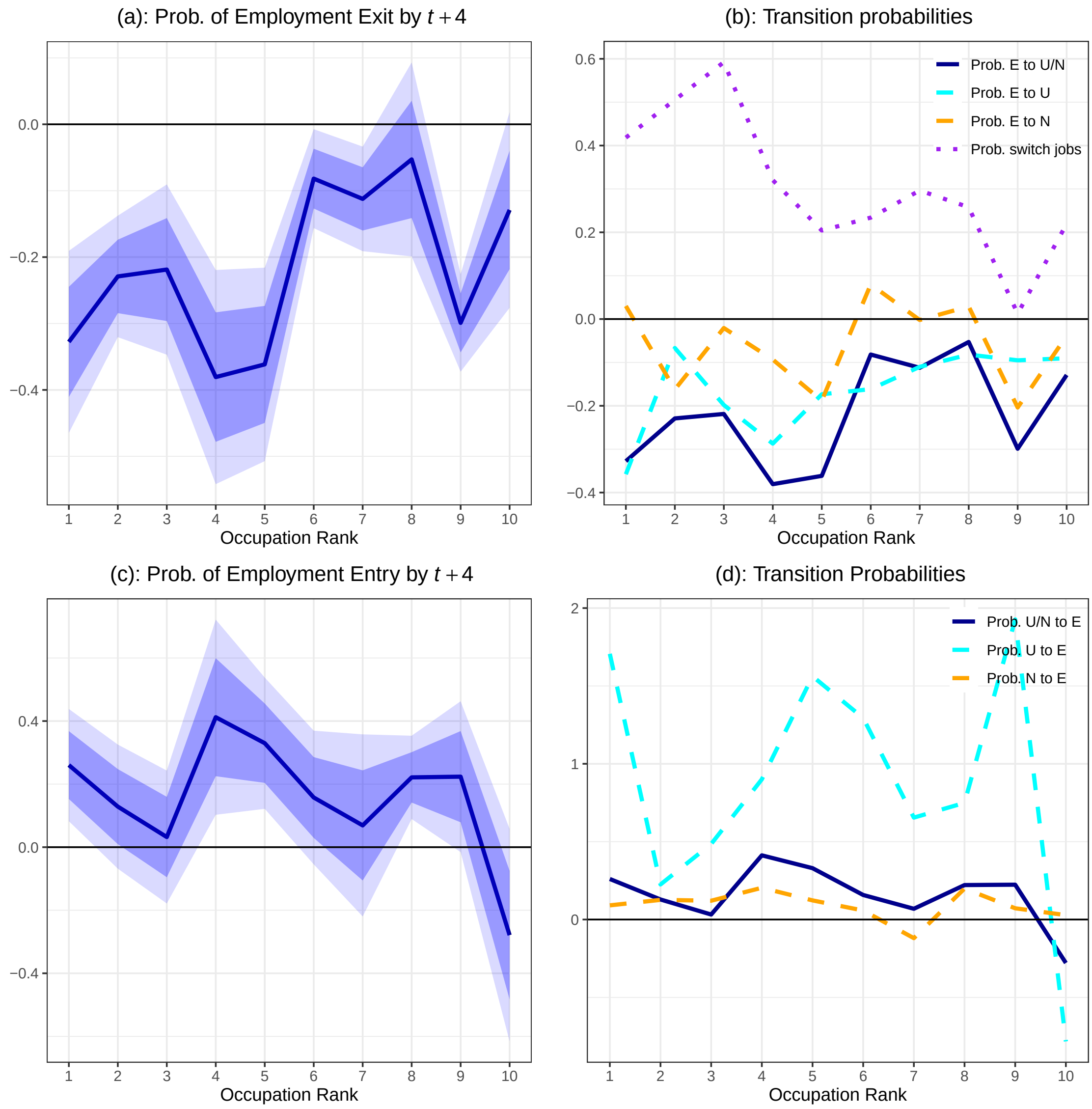
Decompositions of the GDP beta for earnings estimated using these two alternative groupings are presented in Figure 5 and discussed in Section 4.

Figure C.3.1 displays the GDP betas for employment exit and entry probabilities estimated using the ranked occupation groups. In particular, panel (a) plots the plots the GDP beta for the linear probability of moving from employment in period t to non-employment in period $t+4$. The response of the employment exit probability is broadly upward sloping across the distribution, providing support to our main results. Panel (b) decomposes the probability of moving out of employment by showing the point estimates for the linear probability of becoming unemployed (cyan line) and the probability of becoming inactive in the labour market. We also plot the probability of switching jobs (purple line). These results also provide support to our main findings. Namely that the unemployment margin again appears to be the primary driver of the overall employment exit response, and the GDP betas for job switching are downward sloping across the income distribution.

Panel (c) plots the plots the GDP beta for the linear probability of moving from non-employment in period t to employment in period $t+4$. This is a margin of adjustment that we are unable to consider in our main empirical approach, given that we include only those employed in the first period of observation. We find that the employment entry response to GDP fluctuations is positive and significantly different from zero, and reasonably similar across the distribution. Panel (d) presents the responses of the individual flow rates. We again find that it is transitions from unemployment that are the most impacted by GDP fluctuations. The response, although imprecisely estimated given the small sample size, is reasonably similar across the distribution. For that reason, we choose to use a constant response in calibrating the HANK model outlined in Appendix D, as discussed in the next sub-section.

Figure C.3.2 plots the GDP betas for employment exit and entry probabilities estimated using the age-sex groups. We find that the GDP beta for the probability of employment exit is largest (most negative) for younger and older age groups. The GDP beta for the probability of employment entry is less heterogenous. In both cases, we find that it is the response of

Figure C.3.1: GDP Betas for Labour Market Transition Probabilities: Occupation Ranking



Notes: See notes for Figure 3. Panel (a) plots GDP beta estimates for the probability of employed individuals in t moving to non-employment in $t+4$. Panel (b) repeats the point estimate from panel (a) (in dark blue) and, in addition, shows the response of individual transition probabilities and the job switching probability. Panel (c) plots GDP beta estimates for the probability of non-employed individuals in t moving to employment in $t+4$. Panel (d) repeats the point estimate from panel (c) (in dark blue) and, in addition, shows the response of individual transition probabilities. In all four panels, individuals are ranked according to the average income of their occupation, or previous occupation for those not employed, in t.

transitions to and from unemployment that are the most sensitive to GDP fluctuations.

C.4 GDP betas for the probability of entering employment

In Tables C.4.1 and C.4.2 we report the average GDP beta for the probability of entering employment under our principle identification strategies. We report estimates both for non-employment to employment probabilities and unemployment to employment. The monetary policy unemployment to employment beta was used to calibrate the HANK model detailed in Appendix D. Fluctuations in GDP cause significant effects on employment entry probabilities, with the exception of the supply shock identification. The monetary policy shock identification produced the largest point estimates thought they are not statistically significantly different from the OLS or 'All Shocks' estimates. Overall, unemployment to employment transitions are more sensitive to GDP fluctuations.

Table C.4.1: Entry Betas (NE to E)

Identification :	OLS	All Shocks	Monetary Policy	Supply
β	0.156**	0.082	0.414**	0.097
	(0.075)	(0.099)	(0.194)	(0.184)
constant	0.076***	0.078***	0.071***	0.077***
	(0.002)	(0.003)	(0.004)	(0.004)
F-stat	9.62	114	16.4	0.76

Notes: Table shows results from the regression $\mathbf{1}_{NE,t,t+4} = \Delta GDP_{t+4} + \epsilon_t$. HAC standard errors reported: *p<0.1; **p<0.05; ***p<0.01.

Table C.4.2: Entry Betas (U to E)

Identification :	OLS	All Shocks	Monetary Policy	Supply
β	0.872***	0.932**	2.179***	0.692
	(0.244)	(0.428)	(0.677)	(0.718)
constant	0.344***	0.343***	0.320***	0.348***
	(0.008)	(0.011)	(0.015)	(0.016)
F-stat	9.79	4.86	14.79	1.243

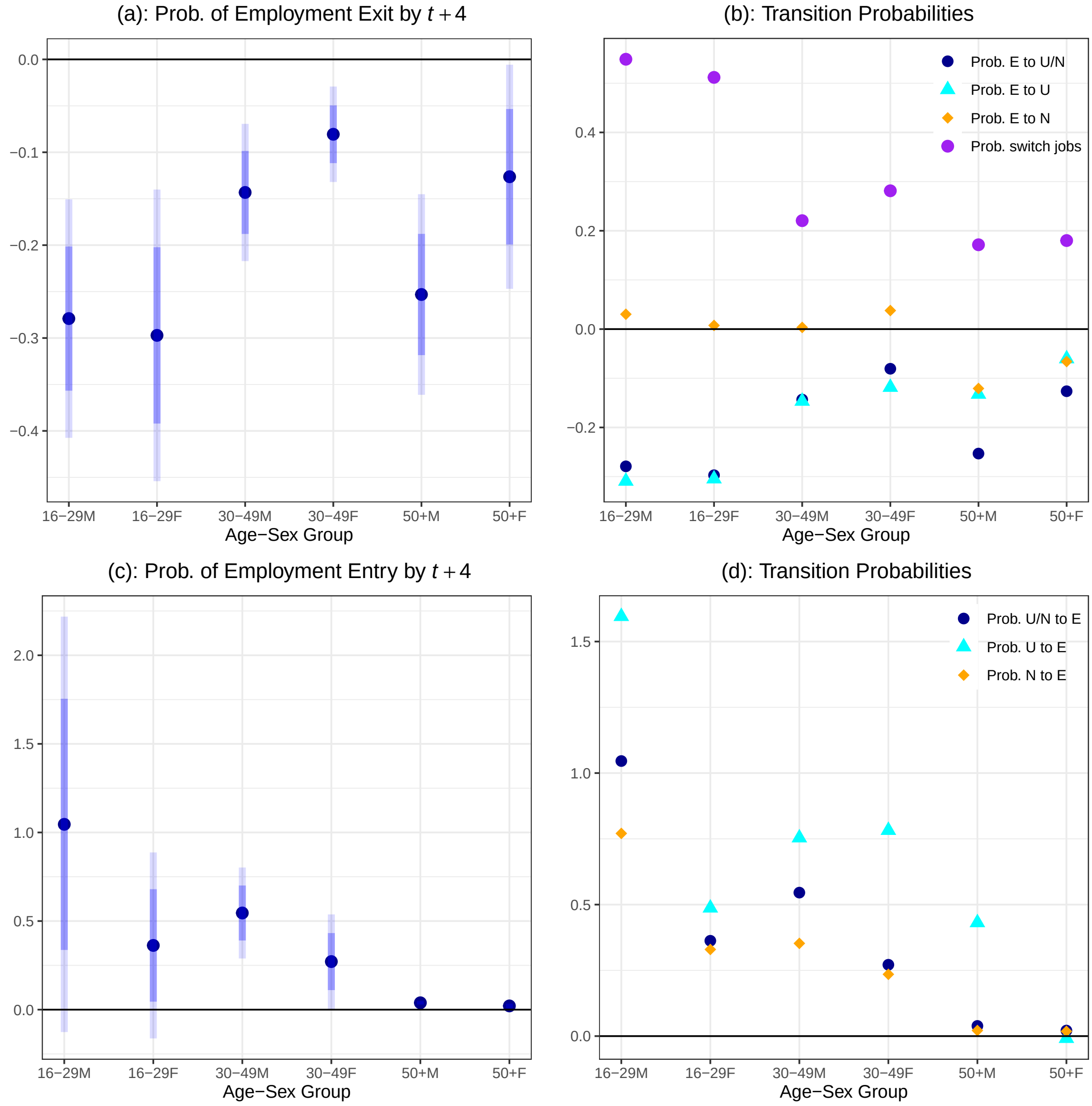
Notes: Table shows results from the regression $\mathbf{1}_{UE,t,t+4} = \Delta GDP_{t+4} + \epsilon_t$. HAC standard errors reported: *p<0.1; **p<0.05; ***p<0.01.

C.5 Household Pay

As a household survey, the LFS interviews each member of selected households which enables us to aggregate our dataset to the household level. It is possible that GDP betas for pay could look different when grouping and sorting by households instead of individuals.[29] For example, individual labour supply decisions are likely to reflect household circumstances e.g. lower labour supply by one member may be compensated for by higher labour supply by another. Figure C.5.1 compares the overall GDP beta for pay for individuals (blue dashed line) to a similar estimate conducted at the household level (purple line and shading). For most pay deciles, the estimated GDP betas are not significantly different from each other. In fact, the principle

[29]The majority of the related literature has conducted its analysis at the individual level.

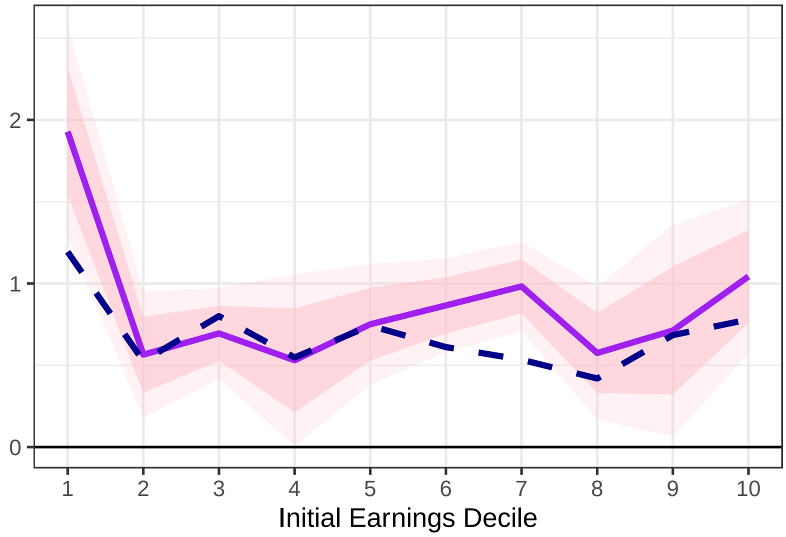
Figure C.3.2: GDP Betas for Labour Market Transition Probabilities: Age-Sex Groups



Notes: See notes for Figure 3. Panel (a) plots GDP beta estimates for the probability of employed individuals in t moving to non-employment in $t+4$. Panel (b) repeats the point estimate from panel (a) (in dark blue) and, in addition, shows the response of individual transition probabilities and the job switching probability. Panel (c) plots GDP beta estimates for the probability of non-employed individuals in t moving to employment in $t+4$. Panel (d) repeats the point estimate from panel (c) (in dark blue) and, in addition, shows the response of individual transition probabilities. In all four panels, individuals are grouped by their reported age and sex in t.

difference between the two point estimates indicates greater sensitivity at the very bottom when sorting and aggregating by household. Outside of the bottom decile, the overall profile is flatter and even upward sloping between deciles four and seven suggesting that some of the hypothesised within household insurance may be present.

Figure C.5.1: GDP Betas for Household Pay



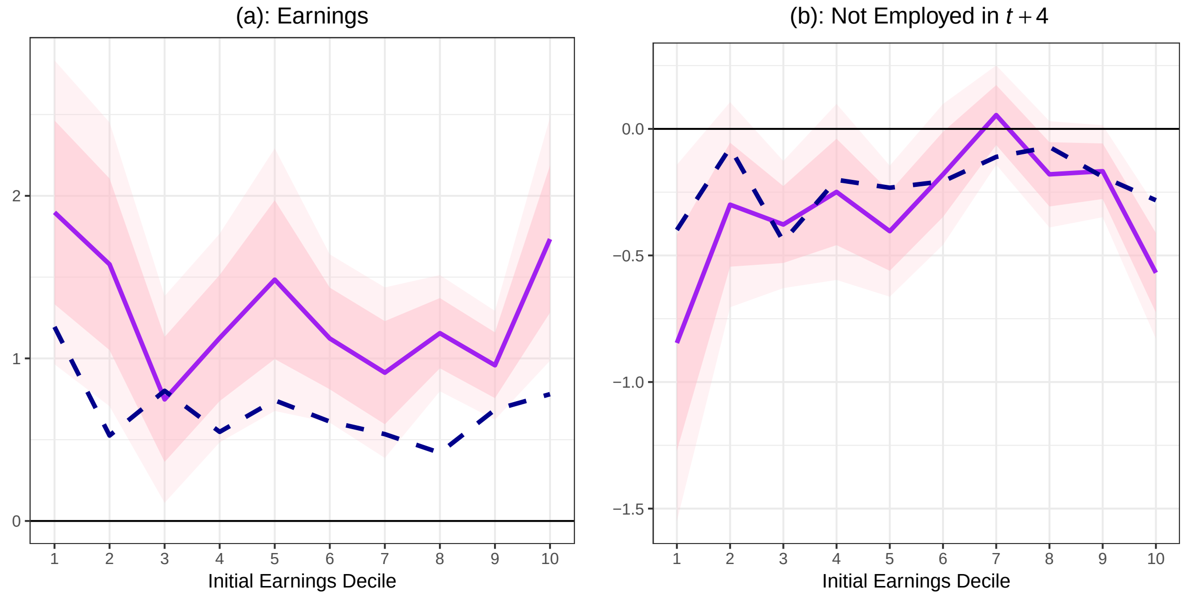
Notes: The purple line plots the coefficients β_g from Equation (2) but aggregating and binning at the household level rather than the individual level. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. Households are sorted into deciles in each quarter based on household earnings in t. The blue dashed line repeats the estimate from Figure 2 panel (a). The sample period is 1997Q2-2019Q4. HAC standard errors reported.

C.6 Recessions

In this sub-section we assess whether controlling for (discounting) periods of negative growth, and in particular the Great Recession, affects our GDP beta estimates. We do this by including indicators of negative growth between periods t and $t + 4$ as an interaction term with GDP growth in Equation (2). Figure C.6.1 plots the estimated GDP betas from specifications which include this interaction term in purple. The point estimates from Figure 2 panel (a) and Figure 3 panel (a) are included as the blue dashed lines for comparison. Overall we see that the point estimates of the GDP betas for pay excluding the impact of recessions are largest at the bottom and smallest in the upper middle. The estimated average GDP beta across the distribution is larger, as also reported by Bell et al. (2022). This suggests that real labour incomes are more sensitive to positive than negative shocks, which is consistent with studies that find evidence of downward real and nominal rigidity.[30] Focusing on the extensive margin (panel (b)), the estimated profile is close to that from our baseline specification.

[30]See Grigsby et al. (2021) and references therein.

Figure C.6.1: Impact of Recessions on GDP betas



Notes: Panel (a) and panel (b) plot GDP beta estimates β_g that control for the impact of recessions by including a negative growth indicator as an interaction term: $y_{g,t,4} - y_{g,t,0} = \alpha_g + \gamma_g \mathbf{1}_{\Delta GDP_{t+4}<0} + \beta_g \Delta GDP_{t+4} + \beta_{g_-} \Delta GDP_{t+4} \mathbf{1}_{\Delta GDP_{t+4}<0} + \epsilon_{g,t}$. The purple lines plot the estimate that controls for periods of negative growth which are compared to the full sample estimates in the blue dashed lines. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4. HAC standard errors reported.

D HANK Model

This section further describes the HANK model discussed in section 5. The model follows Auclert et al. (2024) and we point the reader to that paper for more detailed derivations. Below we report the key model equations and describe the household problem. We also estimate some selected dynamic parameters to bring the model dynamics in line with the dynamics of the SVAR in section B. The model is solved in the sequence space following the methods of Auclert et al. (2021).

D.1 Model Equations

D.1.1 Household Problem

Agents differ in their discount factors and productivity levels. Agents may not borrow, but can save in a liquid account that pays interest rate r. The household's recursive problem can be written as:

$$V(z_t, a_t, X_t, \beta_{i,t}) = \max_{c_t, a_{t+1}} u(c_t, h_t) + \beta_{i,t} \mathbf{E}_t V(z_{t+1}, a_{t+1}, X_{t+1}, \beta_{i,t+1} | z_t, X_t, \beta_{i,t}), \tag{D.1.1}$$

subject to

$$\begin{aligned} a_{i,t+1} + c_{i,t} &= (1 + r_t) a_{i,t} + z_i(X_t) h_t w_t (1 - \tau_t) + T_G \\ a_{i,t+1} &\geq 0 \end{aligned}$$

where a represents assets, z is agent productivity that also depends on the aggregate state of the economy X, c is consumption, w is the wage rate, h is hours worked, T_G is a government transfer, and $\beta_i \in \beta_L, \beta_H$ is the agent-specific discount factor.[31] The utility function takes the form:

$$u(c,h) = \log(c_t) - \psi_l \frac{1+h^{\psi}}{1+\psi} \tag{D.1.2}$$

Agents experience disutility from labour but the labour supply choice is determined for all agents by a union that acts on their behalf. The optimality condition for each agent is then described by:

$$u_c(c_t) = \beta_{i,t} E_t[(1+r_{t+1})u_c(c_{t+1})] + \lambda_t \tag{D.1.3}$$

where λ_t is the lagrange multiplier on the budget constraint.

D.1.2 Other Equations

The rest of the model equations define endogenous outcomes for production Y, the output gap $\hat{y}$ defined relative to steady state labour supply.[32], labour services L, the Dividend D, real wage w, stock price q, wage π_w and price inflation π, government debt B, and the interest rate i_t/r_t:

Labour services: $L_t = h_t \int_i z_{i,t} di$

Production: $Y_t = Z_t L_t$

Output Gap: $\hat{y}_t = \frac{Y_t - Z_t L_{ss}}{Z_t L_{ss}}$

Real wage: $w_t = \frac{Z_t}{\mu}$

Dividend: $D_t = (1-\tau)(Y_t - w_t L_t)$

Stock price: $q_t = E_t[\frac{D_{t+1}+q_{t+1}}{1+r_{t+1}}]$

Wage Philips curve: $\pi_{w,t} = \bar{\beta} E_t[\pi_{w,t+1}] + \kappa_w \int_i \phi_l h_t^{\psi} - w_t(1-\tau_t) z_{i,t} c_{i,t}^{-\sigma} di$

Price inflation: $(1+\pi_t)(1+\frac{w_t}{w_{t-1}}) = 1 + \pi_{w,t}$

Government Debt: $B_t = B_{t-1}(1+r_t) + G + T_G - \tau_t Y_t$

Tax rate: $\tau_t = \tau_{ss} + \gamma_\tau \frac{B_{t-1} - B_{ss}}{Y_{ss}}$

Interest rate: $i_t = (1-\rho_i)(r_{ss} + \phi_\pi \pi_t + \phi_y \hat{y}_t) + \rho_i i_{t-1} + \epsilon_{r,t}$

Real interest rate: $1 + r_t = \frac{1+i_{t-1}}{1+\pi_t}$

Asset market: $\int_i a_{i,t} di = B_t + q_t$

[31] Two discount factors allows us to calibrate to a specific aggregate MPC.

[32] In the analysis we focus on the response to a monetary policy shock whereby potential GDP equals the steady state level. We define relative to steady state labour supply to accommodate movements in TFP and simply assume there is no change in labour supply which is not far off the mark under log utility and Frisch elasticity of 1.0.

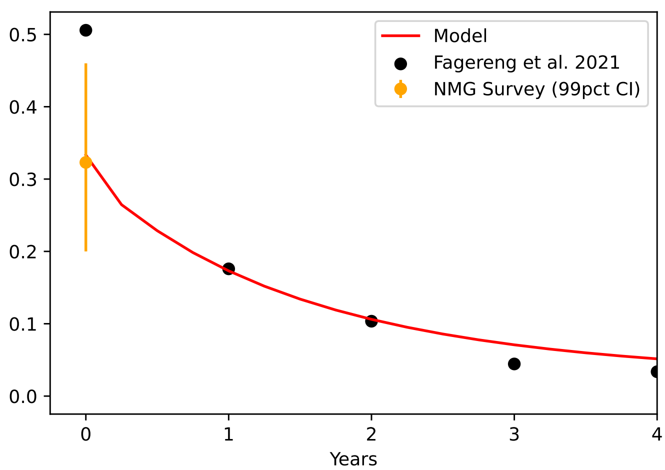
D.2 Calibration

In selecting model parameters we generally follow the parametrisation strategy of Auclert et al. (2024). We deviate however for certain parameters in order to better fit UK macroeconomic data over the sample period 1997-2019. The models steady state labour market transition rates combine to produce a steady state unemployment rate of 5.92%.

Table D.2.1: Calibrated Parameters

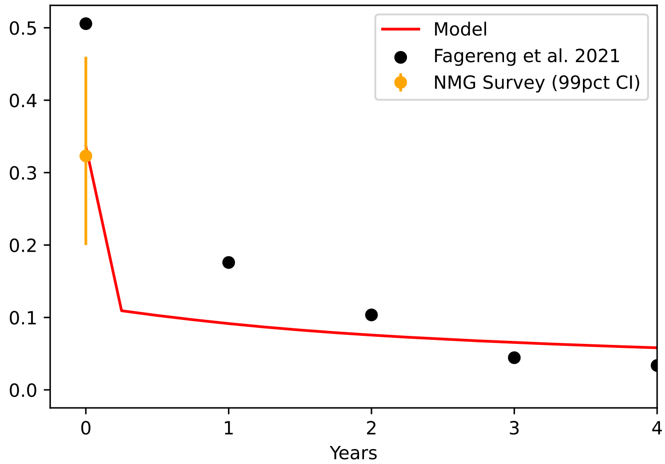
Parameter	Value	Description	Moment / Source / Target
σ	1.0	CRRA (Inverse EIS)	Auclert et al. (2024)
ψ	1.00	Inverse Frisch elasticity	Auclert et al. (2024)
ϕ_l	1.17	Labour disutility wgt	Steady state Labour supply = 1.0
β_l, β_h	(0.962,0.997)	Discount factors	$iMPC_0 = 0.32$, NMG Survey.
q_β	0.01	Prob. of new β draw	Auclert et al. (2024)
ω_β	0.49	Prob. of β_h	Auclert et al. (2024)
r_{ss}	$\frac{0.02}{4}$	Interest rate	Auclert et al. (2024)
π_{ss}	0.0	Steady state inflation	Auclert et al. (2024)
B_{ss}	0.72	Government Debt	Avg. Gov. liabilites (NIJT) to GDP (1997-2019)
G	0.19	Government spending	Avg. Gov. purchaes (NMRP) to GDP (1997-2019)
T_G	0.06	Government Benefit	Avg. social assistance pmt. (HAYU) to GDP (1997-2019)
τ	0.264	Tax rate	Balanced budget in steady state
μ	1.04	Price markup	Avg. net financial asset to GDP ratio (ONS, 1997-2019). $\frac{A}{4Y} = 2.0$.

Figure D.2.1: Average iMPCs



Notes: Figure plots the consumption response in the model to an unanticipated lump sum transfer. This is compared to the values reported in Fagereng et al. (2021) based on lottery results, and the values reported in the Household NMG 2013 survey based on responses to hypothetical question: If your household received an unexpected windfall of £500 tomorrow, what do you think you would do with this extra money over the next year? We also plot the corresponding response to a negative income shock.

Figure D.2.2: Average iMPCs (No Extensive Margin)



Notes: Figure plots the consumption response in the model to an unanticipated lump sum transfer. This is compared to the values reported in Fagereng et al. (2021) based on lottery results, and the values reported in the Household NMG 2013 survey based on responses to hypothetical question: If your household received an unexpected windfall of £500 tomorrow, what do you think you would do with this extra money over the next year? We also plot the corresponding response to a negative income shock.

D.3 IRF Matching

Table D.3.1: Dynamically estimated parameters

Parameter	Value	Description
$1-\gamma$	0.12	Household's probability of updating forecast.
ϕ_τ	0.21	Fiscal adjustment speed
κ_w	0.09	Wage philips curve slope
ρ_i	0.80	Taylor rule inertia
ϕ_π	2.5	Taylor rule inflation coef.
ϕ_y	0.0	Taylor rule output gap coef.

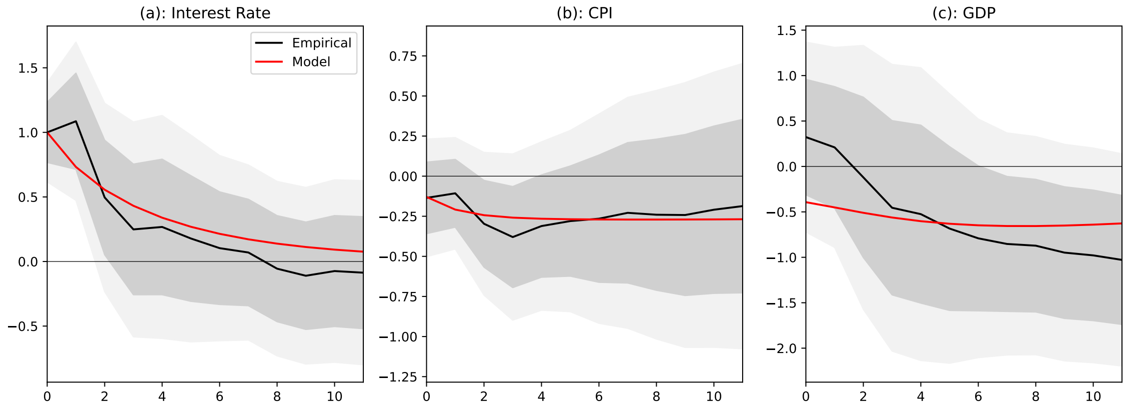
We further calibrate the model by estimating a set of parameters θ_{IRF} relevant for the models dynamics by minimising the weighted difference between model impulses responses Y and the empirical counterparts $\dot{Y}$.

$$MIN_{\theta_{IRF}}(Y(\theta_{IRF}) - \dot{Y})^T W (Y(\theta_{IRF}) - \dot{Y}) \tag{D.3.1}$$

We take as our empirical evidence the impulse response estimated in section B. W is set as the inverse of the standard deviation of the impulse response with zero weight given to responses beyond 12 quarters.

Table D.3.1 reports the estimates for the dynamic parameters with Figure D.3.1 illustrating the model responses to a monetary policy shock relative to the empirical evidence. We implement departures from rational expectations by manipulating the relevant Jacobians following Auclert et al. (2020). Specifically we model households as having sticky expectations where they only update price forecasts with probability $1-\gamma$. This allows us to better capture the hump shaped response of the empirical impulse responses as advocated in Auclert et al. (2020).

Figure D.3.1: Impulse Response to a Monetary Policy Shock



Notes: Figure reports the impulse response to a 1pp unanticipated monetary policy shock. The black line and shaded areas are the paths from the SVAR estimates averaged to a quarterly frequency. The shaded areas represent the 68% and 90% confidence intervals for the empirical responses.

D.4 Beta and precautionary saving contributions

The sequence space jacobian solution method allows for easy decomposition of general equilibrium outcomes into partial equilibrium channels in response to shocks. Consider an outcome $Y(x)$ in the sequence space that depends on vectors of inputs x also in the sequence space. Then the response of Y to a shock ϵ can be expressed as follows:

$$\frac{dY}{d\epsilon} = \sum_x \frac{dY}{dx}\frac{dx}{d\epsilon} \tag{D.4.1}$$

The above equation shows how changes in Y can be attributed to channels in x and the impulse response of x to ϵ. In the case of the decompositions in section 5, Y is consumption and x is the vector of inputs relevant to the households consumption decision. This includes the current and expected future output gap $\hat{y}$, which affects z. We can further decompose the effect by defining two output gaps $\hat{y}$ and $\hat{y}_{ext}$. These are always equal in general equilibrium, but in the household problem separately affect the intensive and extensive margin of z transitions.

To further define and decompose the precautionary savings channel, we can divide the Jacobians J of consumption with respect to the output gap, wages and hours worked into Jacobians with respect to current and past changes in x, and expected future change in x. In practice this means constructing Jacobians from the relevant fake news matrices $F_{Y,x}$ with the first column set to zero. This gives us a Jacobian purely related to the news effects which we call the precautionary saving effect. See Auclert et al. (2021) for more detail on how to construct a fake new matrix and derive the sequence space Jacobian from it.