The Impact of Aggregate Fluctuations Across the UK Income Distribution

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Abstract

In this paper, we examine the response of pay 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 heterogeneous impacts across the income distribution. Sensitivity is greatest at the very bottom (first decile) of the income distribution and smallest in the upper middle (seventh and eight deciles) of the distribution. The transmission of GDP fluctuations differs across the income distribution. Changes to hours worked and employment explain the majority of the income response in the bottom half of the distribution, whereas changes to the hourly wage are more important in the top half. In a further decomposition, we show that the changes to employment are largely due to fluctuations in the employment to unemployment transition rate. We also find that GDP fluctuations are positively correlated with job switching in the bottom half of the distribution.

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees.

1 Introduction

What is the incidence of fluctuations in aggregate economic activity? Who experiences changes to their earnings and employment? How important are changes to hourly pay, hours worked and job separations as margins of adjustment?

A relatively recent and growing literature has begun to answer these questions empirically, following Guvenen et al. (2017). We seek to add to this literature by focusing on two aspects that have received relatively less attention to date: (1) a decomposition of changes in labour income into changes in employment, inactivity, hours and hourly pay; and (2) evidence for the UK economy. We do so using microdata from the UK's Labour Force Survey (LFS), which is the largest household survey in the UK and underpins the UK's national labour market statistics. Our empirical approach takes advantage of the short panel element of the LFS, whereby individuals remain in the survey for up to five quarters. We estimate OLS regressions of changes in pay or labour market status on changes in Gross Domestic Product (GDP) over the same period. These regressions are estimated by initial pay decile and we refer to the coefficients on changes in GDP as GDP betas. We show that these GDP betas can be best interpreted as elasticities to transitory fluctuations in GDP. Overall we find:

(i) Statistically significant GDP betas for pay and employment across the income distributions.

(ii) GDP betas take the form of an incomplete U.

   (a) The largest effects are at the very bottom of the distribution, a group largely composed of part time workers, female workers and students.

   (b) The smallest effects are in the upper middle (seventh and eighth decile) of the income distribution.

   (c) There is also some heightened sensitivity at the top of the distribution.

(iii) A significant role for movements into unemployment in driving the differences across the income distribution.

   (a) Extensive margin transitions are most important in the bottom half of the distribution.

   (b) In contrast, changes in hourly pay are found to be the most important determinant in the upper middle portion of the income distribution.[1]

   (c) We also find that GDP fluctuations are positively correlated with job switching in the bottom half of the distribution.

These broad descriptions hold for general fluctuations in GDP as well as fluctuations identified using monetary policy shocks or GDP forecast errors from a VAR. We do this in order to more explicitly identify unexpected fluctuations in GDP for comparison with our main results. The response to monetary policy is also of explicit interest given the role of monetary policy in stabilising the economy.

We also compare our GDP beta estimates to average unconditional (or steady state) labour market transition rates across the income distribution. Unlike the average unconditional probability of a transition out of employment, which is largely explained by movement into inactivity, transitions into unemployment explain the majority of employment exits associated with the business cycle.

[1]Reported gross labour earnings deflated by the GDP deflator.

In further analysis, we find that whether grouping at the individual or household level, the overall pay betas are similar and our broad conclusions hold. Similarly, our conclusions are unaffected when we exclude those initially part-time employed from our sample. In fact, excluding part-time workers makes our conclusions clearer across the income distribution. We also check whether controlling for negative GDP growth periods, such as the great recession, changes our results, but again find that our broad conclusions are unchanged.

We analyse the variance of pay growth across the income distribution and show that extensive margin transitions explain the differences that we observe. We also estimate a negative GDP beta for pay growth variance across the distribution. This follows from the correlation between GDP fluctuations and extensive margin labour market transitions, with increases in GDP reducing the probability of movements out of employment.

Our results will be of interest to fiscal and monetary policy makers in helping inform them of the potential distributional implications of any policy changes that may impact the aggregate business cycle.[2] The facts presented in this paper will also be noteworthy for economic modellers seeking to calibrate macroeconomic models that incorporate meaningful heterogeneity at the business cycle frequency to analyse the implications of fiscal and monetary policy e.g models in the HANK literature following from McKay & Reis (2016).[3]

1.1 Related Literature

As mentioned, this paper fits into a growing literature that seeks to understand the distributional implications for households and individuals 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 across the income distribution, with the incomes of the poorest and richest individuals found to be most exposed to the US business cycle in the US. 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 using administrative data from Sweden, Denmark and Norway respectively.[4] 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 the top.

The literature has mostly focused on the response of incomes, but some papers such as Broer et al. (2022) 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. Broer et al. (2022) similarly find that the extensive margin is key to explaining the excess sensitivity to the business cycle at the bottom of the distribution. We contribute to this aspect of the literature by focusing on adjustment along both the intensive and extensive margins, and a more granular decomposition of extensive margin adjustment into the transitions into inactivity and unemployment, and also to job mobility.

In terms of the UK, Bell et al. (2022) use the Annual Survey of Hours and Earnings 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. Cantore et al. (2022) 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

[2]Particularly UK policy makers, advisers and economic modellers.

[3]Including the descriptive statistics.

[4]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.

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. Compared to this study, we leverage the panel element of the LFS, focus on a more recent sample (1997-2019) that is more representative of the bottom of the income distribution and focus on the broader business cycle.

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 and section 5 concludes.

2 Data and Descriptive Statistics

2.1 Data

This study focuses on data from the UK's Labour Force Survey (LFS). The LFS is the largest household survey in the UK and is used to construct the 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.1.1.

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, our analysis is conditioned on 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 this 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.

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
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

Note: 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. 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).

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

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

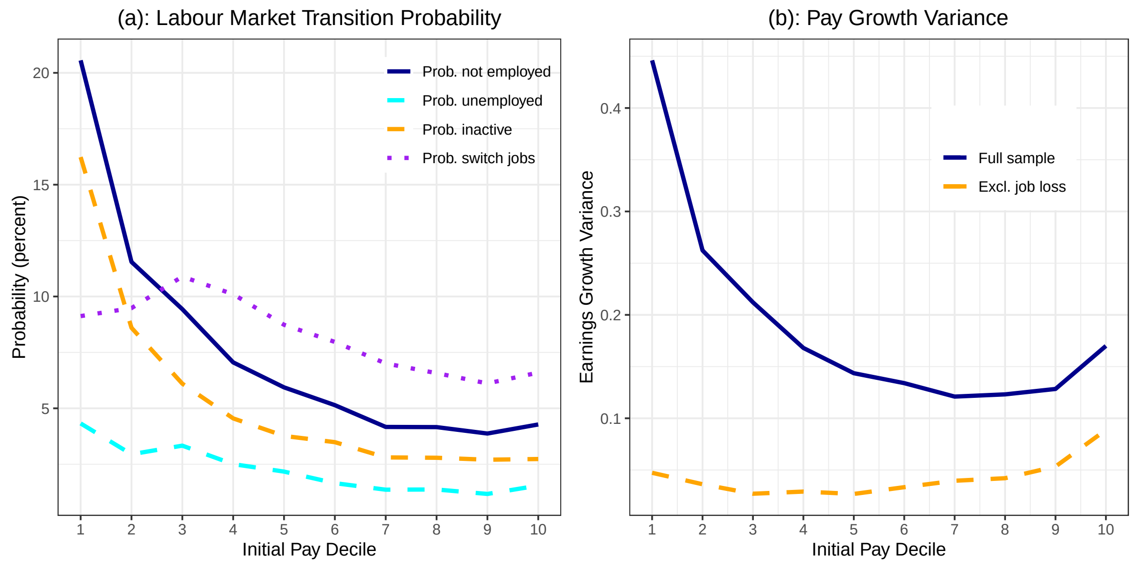
where g is an income group, i is an individual in the LFS, quarter $t+h, h \in \{0,4\}$, $w_{i,t}$ is the LFS income weight of individual i at time t and y is a variable of interest, e.g. labour earnings or an employment indicator.[5]

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.[6] 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 lower 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 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.

[6]HMRC Survey of Personal Incomes.

Figure 1: Further Unconditional Moments



Note: 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.

share of students stands out in the bottom income bucket.

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.[7] 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 also notable that even in the middle and upper deciles, transitions between jobs or into non-employment are still quite common. This underscores the value of being able to follow individuals in a panel as opposed to conducting analysis on a pseudo-panel (e.g. Verbeek (1996)), where this margin is either omitted or imputed. In terms of movements along the income distribution between waves, in further analysis (see Appendix A.1.2) we find that the large majority of individuals either remain in the same income decile or move into adjacent deciles.

[7] 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.

3 Empirical Framework

Our empirical approach follows the example of other similar work, such as Guvenen et al. (2017) or Broer et al. (2022), by running regressions of annual changes in different outcome variables on aggregate changes in GDP by income decile. We refer to the elasticity, β_g, resulting from these regression as a GDP beta. The outcomes that we consider are: 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.[8] 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 trend growth and the elasticity to transitory business-cycle frequency fluctuations.

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

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

where the change in GDP is $dgdp_t = dg_t + da_t$ is composed of a slow moving trend growth 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 then estimate the regression:

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

we will attain 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 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), 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.

In addition to the approach outlined above, we also estimate GDP betas by trying to isolate more transitory business cycle frequency movements in GDP. We do so because it may be the case that the responses to transitory shocks are 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 its self and a focus of the related literature. To do so, we estimate Equation (2) via two stage least squares, instrumenting for changes in GDP with either accumulated

[8]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.1.1.

monetary policy shocks prior to time t or the unexpected component of GDP growth between period t and $t+4$.[9] Both methods draw upon a six variable VAR outlined in Appendix A.2, with the first stage explaining a significant share of movements in GDP as indicated in Table A.2.1.[10]

4 Results

4.1 GDP Betas

Our main estimates of β_g from Equation (2) for pay and hours are displayed in panels (a) and (b) of Figure 2. Despite some volatility at the bottom, the overall picture is of a downward sloping GDP beta estimate as we move across the distribution from the lowest income groups to the higher incomes groups, with some reversal as we move past the lowest variance income groups (deciles 7 and 8).[11] The average pay beta is around 0.6, which is similar to the estimate in Bell et al. (2022) using a longer sample of UK earnings data.

The different shape of the GDP beta distribution for pay and hours displayed in panels (a) and (b) of Figure 2 suggests that the margin of adjustment to fluctuations in aggregate conditions may vary across the income distribution. In panels (c) and (d) of Figure 2, we therefore present decompositions of the GDP beta estimates. 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 that remain employed in period t and $t+4$. The estimated betas for those that remain employed is uniformly below the whole sample estimates, and by a large margin for some income deciles. This points to an important role for the extensive margin in accounting for the sensitivity of pay 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 significantly different 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) focuses on those that remain employed in both periods (the orange line) and approximately decomposes the GDP beta point estimate into changes in hourly pay and changes in hours.[12] The purple dashed line plots the hours beta for those that remain employed and shows it to be downward sloping across the income distribution. This contrasts with hourly pay (green dashed line) which, though more volatile, is roughly upward sloping; it explains a smaller share than hours at the bottom of the distribution and almost the entire adjustment from the middle to the top of the distribution.

The results in Figure 2 point to an important role for the extensive margin in determining the sensitivity of incomes across the UK income distribution. In Figure 3 we therefore further investigate this margin of adjustment by using labour market transitions as the outcome variables on the LHS of 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 percent change in GDP is associated with around a 0.2 percentage point reduction in the probability of moving to non-employment on average across the distribution. With the exception of decile 2, the absolute value of the non-employment GDP betas is larger in the bottom half of the distribution

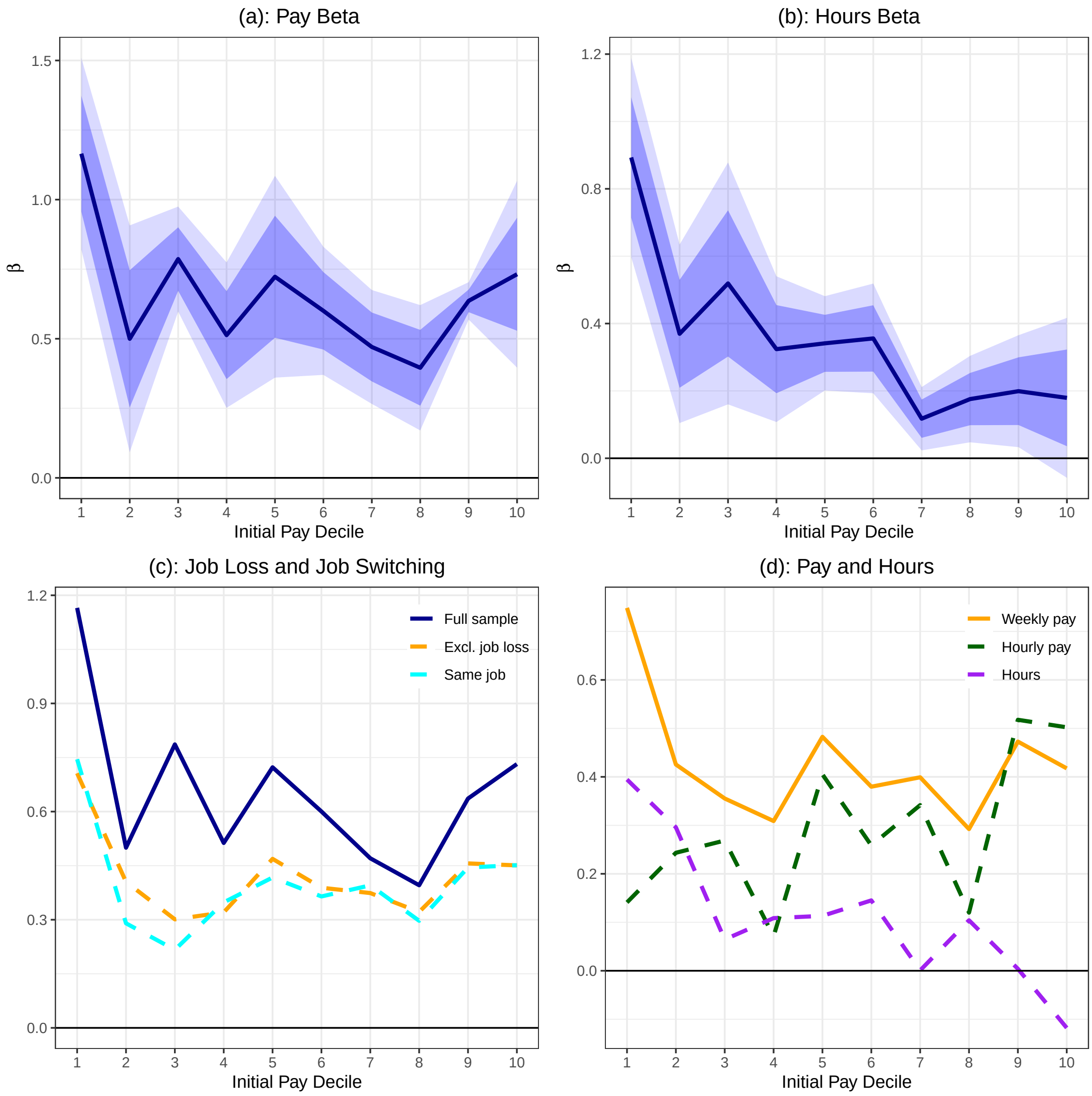
[9]We use high frequency shocks identified in 30 minute windows around MPC instruments and focus on movements in the three month short sterling futures contract expiring 3-6 months after the announcement (see Cesa-Bianchi et al. (2020) for more details). To instrument for changes in GDP we use accumulated shocks from one and two years prior in line with the significance of the transmission dynamics captured in the VAR illustrated in Figure A.2.1.

[10]F statistic of 11.1 and 40.3 for the monetary policy shocks and forecast error approach respectively.

[11]See Figure 1, panel (b).

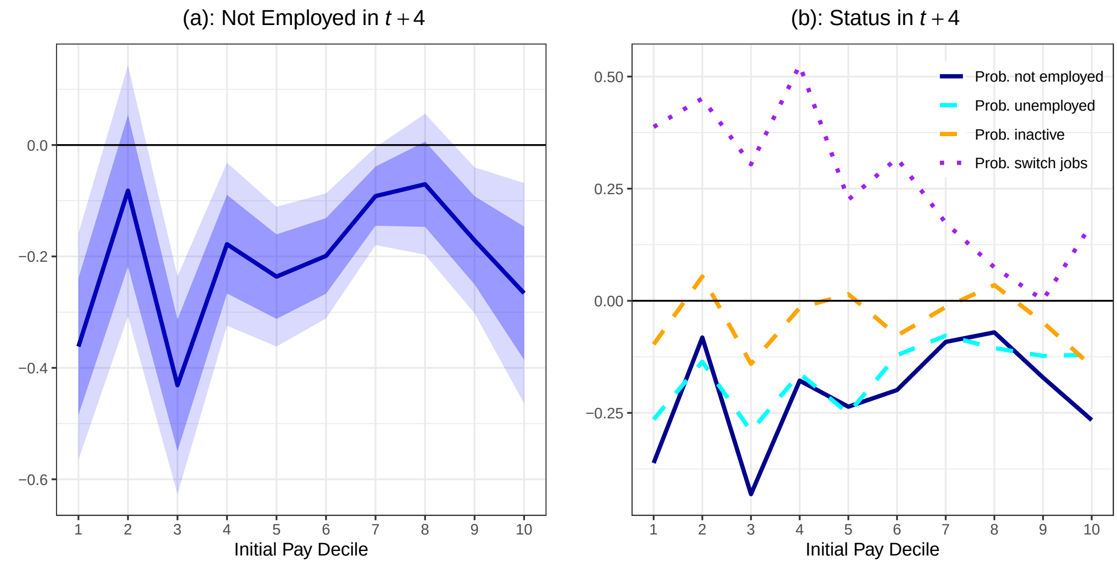
[12]Whilst close in practice, the product of the arithmetic weighted mean of the change in hours and change in hourly pay does not equal the arithmetic weighted mean of the change in pay (hours x hourly pay).

Figure 2: Pay and Hours Betas



Note: Panel (a) plots the coefficients β_g from Equation (2) for changes in labour income and panel (b) for changes in hours worked in their main job. The darker (lighter) shaded area represents the 68% (90%) confidence intervals 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 again 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) plots the coefficients β_g from Equation (2) with different dependent variables, for the sample of individuals that are employed in both periods: the orange line plots the coefficients using weekly pay as the dependent variable, as in the orange line in panel (c); the green line plots the coefficients using hourly pay as the dependent variable; the purple line plots the coefficients using weekly hours worked as the dependent variable. 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: Labour Market Transition Betas



Note: 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.

and smallest at the lowest variance points of the income distribution before becoming more negative again at the very top.

It's not clear whether the estimated betas for decile 2 in panel (a) of Figures 2 and 3 reflect genuine differences or unobserved sampling volatility. Cantore et al. (2022) et al find some evidence of counter-cyclicality of labour supply at the very bottom which could be consistent with this response. From Table 1, we know that those in the first decile work fewer hours and are more likely to be a student or above 60, and therefore may be more marginally attached to the labour force and more sensitive to aggregate economic conditions. Through economic circumstance, those in decile two could be very attached to the labour force and exhibit greater counter-cyclical labour supply. It's notable that when we remove those initially part-time employed from our sample, the results are smoother across the distribution and reinforce our main conclusions (see appendix Figure A.3.2). Again, it's not clear whether this is because data collection is poorer for part-time workers and/or part-time workers are systematically behaving differently to full-time workers.

In panel (b) of Figure 3, we decompose 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). 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 margins 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. 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).

4.2 Transitory Shocks

As discussed in section 3, the beta estimates reported in the previous sub-section reflect a variance-weighted average of trend growth (dg) and more 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 and monetary policy shocks as first stage instruments for GDP growth, as outlined in Table A.2.1. The key results are shown in Figure 4. The first row shows the results for the forecast errors approach. The pattern and magnitudes of the estimates are quite similar to that of our main beta results. The pay beta (panel (a)) is larger in the bottom half of the distribution and lowest in the upper middle. It does, however, tick up more noticeably at the top of the distribution. The extensive margin again plays an important role in determining this pattern (panel (b)).

The bottom row of Figure 4 shows the results for monetary policy shocks. While still elevated at the bottom on the income distribution, the pay beta point estimates in panel (c) are noticeably flatter than for the other estimates, though the confidence intervals around pay are larger. The pattern for the linear probability of non-employment (panel (d)) is more similar to the other results, with heightened sensitivity in the bottom half of the distribution. Taken together with additional results reported in Appendix A.2.1, the overall message of the instrumental variable approach is similar to that of the unconditional approach as hypothesised in section 3.

4.3 Other Exercises

We have also conducted a number of additional exercises which we summarise in this section and further discuss and illustrate in Appendix A.3. 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 pay betas could look different when grouping and sorting by households instead of individuals.[13] 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. Overall though, we don't find a significant difference in our results when grouping at the household level.

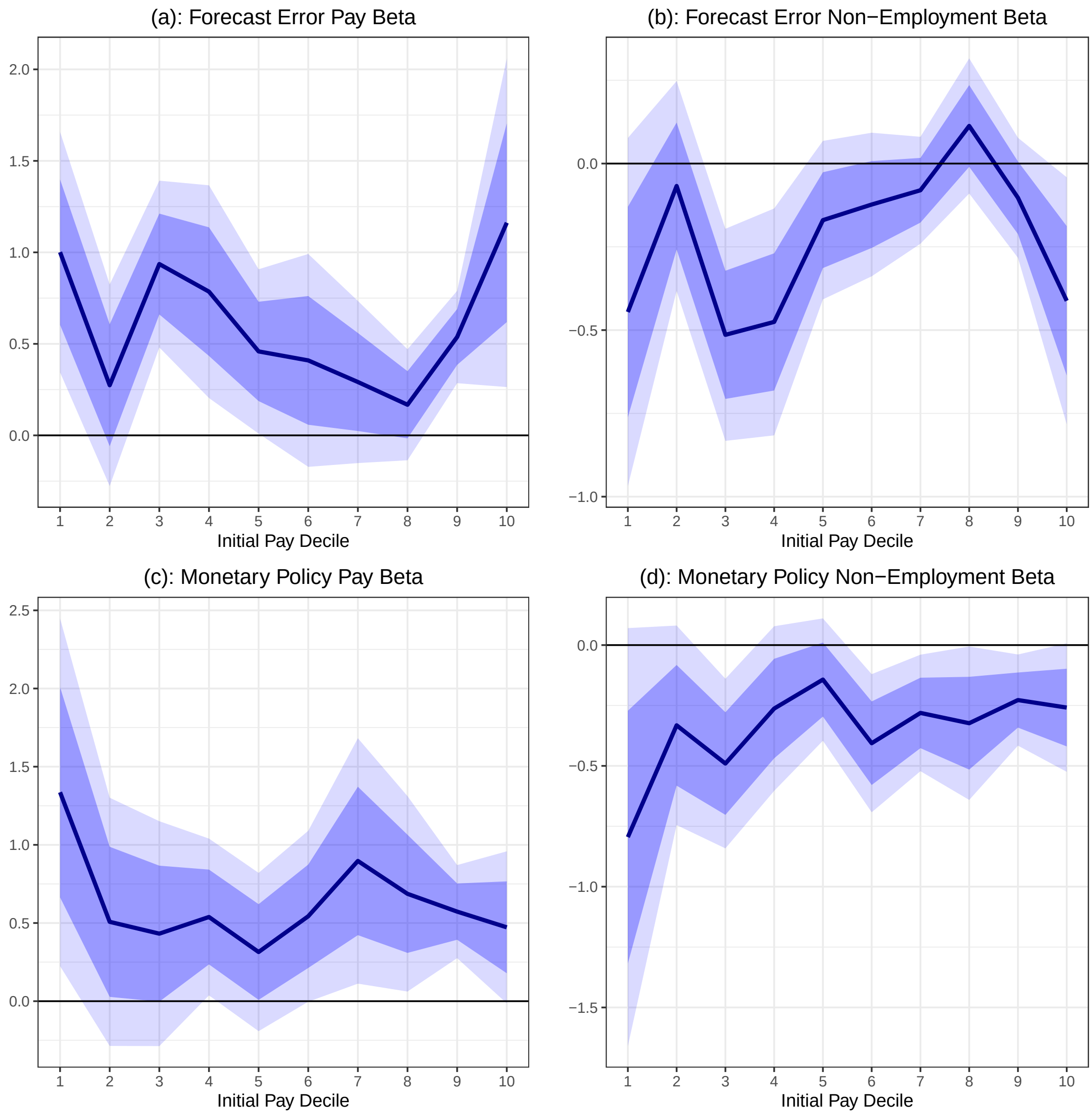
Most of our results have exhibited some volatility and reversals within the first 3 deciles. And as shown in Table 1 there are a large amount of part time employees in these deciles. In order to better understand the role that part time employees may be playing in exaggerating or distorting our conclusions, we removed those initially part-time employed from our sample (period t) and re-estimated our key exercises. The results excluding these part-time employees underscores the conclusions from the previous sections. In particular, the pay beta is slightly more U-shaped and the slope of the non-employment beta is steeper.

We also considered whether controlling for (discounting) periods of negative growth – and in particular the great recession – affects our 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 conclusions from these results are similar to that of our main results, particularly for the extensive margin transitions: we do find some statistically significant differences in the estimated pay betas for some deciles.

Finally, the change in the variance of income growth across the distribution in response to GDP fluctuations is a further object of interest and a theoretically important determinant

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

Figure 4: Betas for Transitory Shocks



Note: Panel (a) and panel (b) plot the coefficients from Equation (2) under an instrumental variable approach using GDP forecast errors from the VAR discussed in Appendix A.2 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. 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.

of household consumption. We find that the pay variance betas are negative across the distribution, and slightly more so in the bottom half. However, the reduction in variance, while statistically significant, is relatively small when compared to the average variances reported in most income deciles in Figure 1.

5 Conclusion

This paper has presented empirical results on the sensitivity of pay and labour market transitions to fluctuations in aggregate economic activity across the income distribution, using data from the UK's Labour Force Survey. We have provided evidence that aggregate fluctuations have statistically and economically significant heterogeneous impacts across the income distribution. In particular, we found greater sensitivity at the bottom of the distribution, which is largely due to the impact on the probability of a transition to unemployment. We also found some evidence of heightened sensitivity at the top of the income distribution relative to the upper middle (4th quintile).

Future research could build on this work by rationalising these GDP betas and steady-state labour market transition rates in a heterogeneous agent economic model of UK business cycles.

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A Appendix

A.1 Data

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

A.1.1 LFS data

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

- **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).

  When grouping individuals into initial income deciles, 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*).

- **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*).

A.1.2 Other data

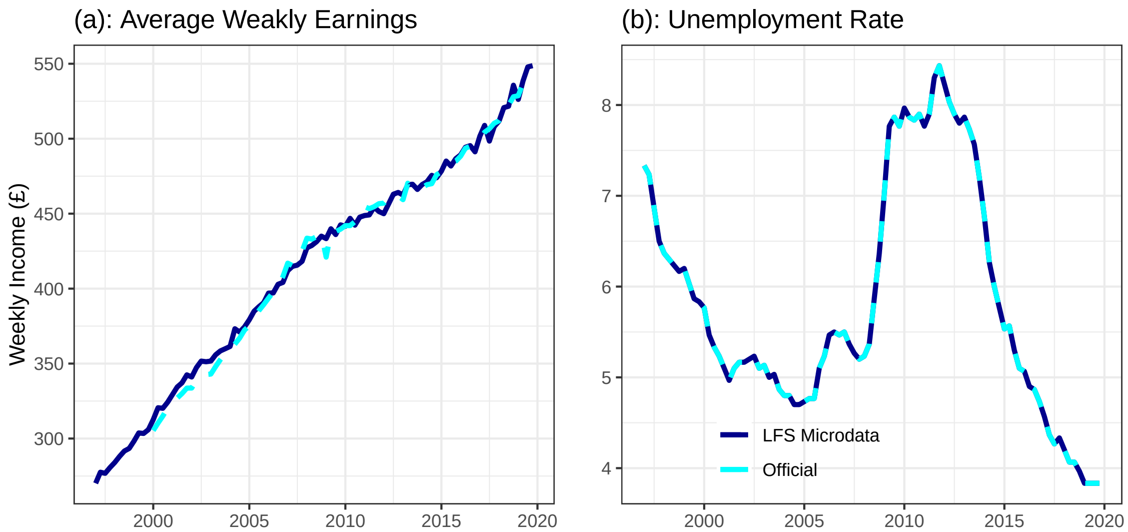
- **GDP**

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

- **GDP deflator**

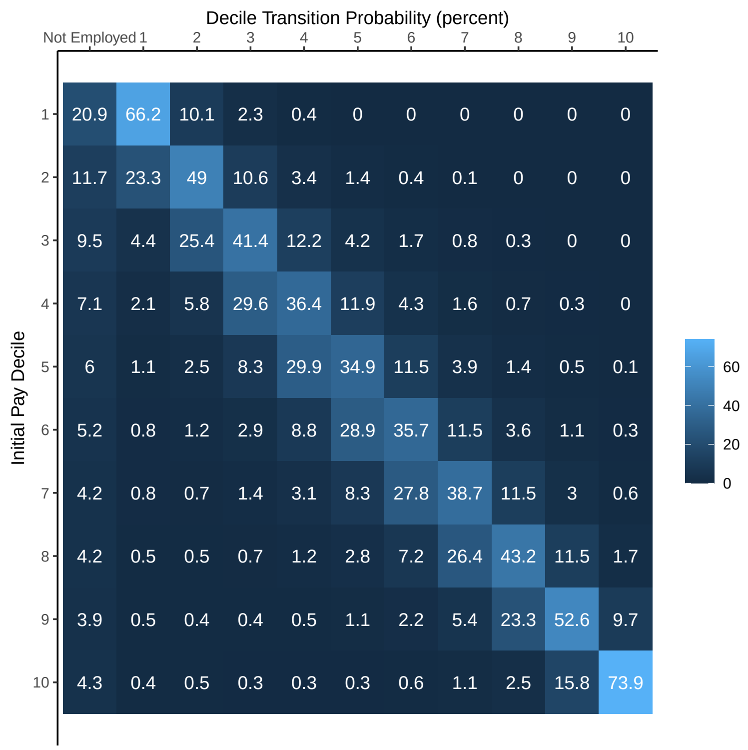
  Latest ONS estimate of the GDP deflator (*YBGB*), used to delate labour income constructed using the LFS data.

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



Note: 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: Pay Decile Transition Matrix



Note: 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.

A.2 Transitory shocks

The SVAR described below supports our analysis by demonstrating the effect of and timing of our chosen monetary policy shocks on GDP, and by providing a framework for forecasting GDP from which we can extract four quarter 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. 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 as it was 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:

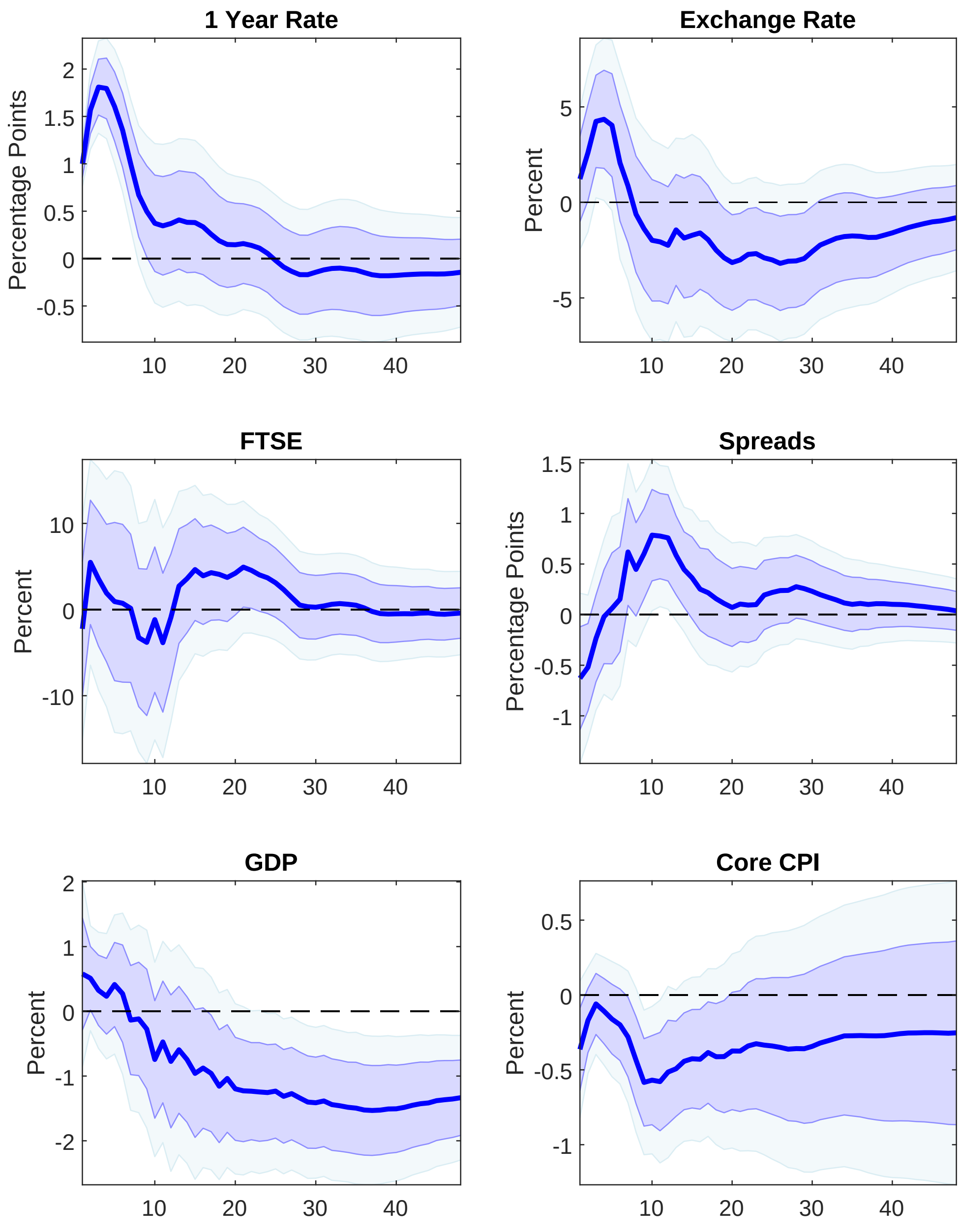
$$\hat{z}_t = \beta x_{t-} + z_t \tag{A.2.1}$$

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 A.2.1 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 percent confidence interval beyond 18 months and 90 percent level beyond 24 months.

When looking to assess the impact of identified transitory shocks in our analysis we do so by estimating Equation (2) via two stage least squares. We instrument for four quarter changes in GDP in two ways. In one approach we sum monetary policy shocks from one and two years prior given the significance of the transmission dynamics captured in Figure A.2.1. In the second approach we use the VAR to forecast GDP growth over the next four quarters and take the residual of that forecast and actual GDP growth as our instrument. This instrument is supposed to reflect the unexpected or surprise component of GDP growth between waves. The results from the first stage regression is outlined in Table A.2.1 where we can see that both approaches are able to explain a significant amount of the variation in GDP growth.

Figure A.2.1: Impulse Response to a 1 Percent Monetary Policy Innovation



Note: Figure shows impulse responses to a 1 percent 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.

Table A.2.1: First Stage Regression on GDP

Instrument:	Monetary Policy Shock	Forecast Error
$z_{1,t}$	-5.95	1.11*
	(3.49)	(0.476)
$z_{2,t}$	-3.79*	
	(2.63)	
constant	0.020***	0.019***
	(0.)	(0.004)
F-stat	11.1***	40.3***
R^2	0.20	0.32

Note: Table shows results from first stage regression $\Delta GDP_{t+4} = \delta z_t + \epsilon_t$. In the monetary policy shock implementation z is accumulated high frequency shocks from one (quarters $t-1$ to $t-4$) and two years prior (quarters $t-5$ to $t-8$). In the forecast error version z is the 1 year ahead GDP forecast error at time t from the VAR detailed in Appendix A.2. HAC standard errors reported: *p<0.1; **p<0.05; ***p<0.01.

A.2.1 Further Results with Transitory Shocks

In this subsection we further decompose the results in Figure 4 as conducted in Figure 2 and Figure 3. Figure A.2.2 and A.2.3 decompose the pay betas for the forecast errors and monetary policy shocks respectively into extensive and intensive margin components. Figure A.2.4 decomposes the extensive margin for each identification approach into movements to unemployment, inactivity and between jobs.

A.3 Additional results

A.3.1 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 pay betas could look different when grouping and sorting by households instead of individuals.[14] 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 A.3.1 compares the overall pay beta for individuals (blue dashed line) to a similar estimate conducted at the household level (purple line and shading). For most pay deciles the estimated betas are not significantly different from each other. There is also no evidence of flattening of the profile across the distribution that within household insurance through labour supply might deliver. In fact, where there are difference between the two lines (deciles 2 and 3), it is in the direction of greater sensitivity at the bottom of the distribution relative to the upper middle.

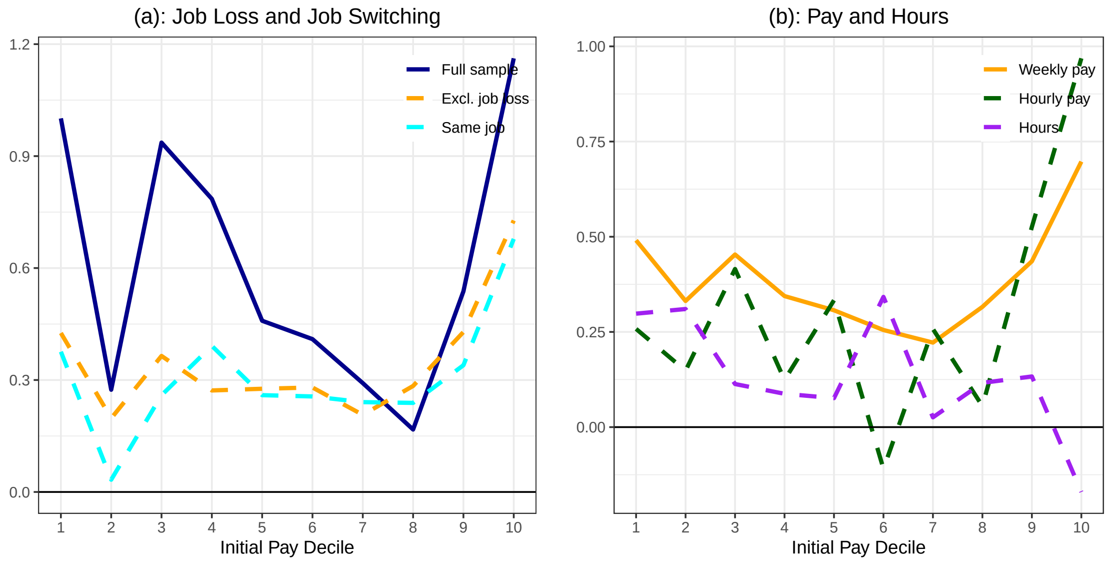
A.3.2 Part Time Employees

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 amount 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.[15] The main results without

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

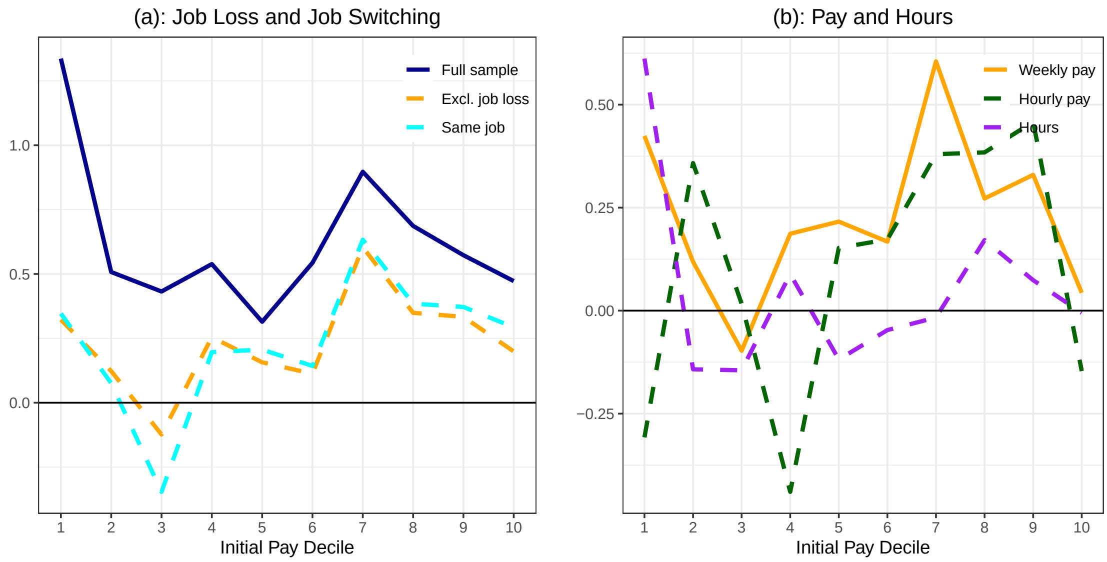
[15] Note employees transitioning to part-time work are still kept in the sample.

Figure A.2.2: Pay Betas Decomposition - Forecast Errors



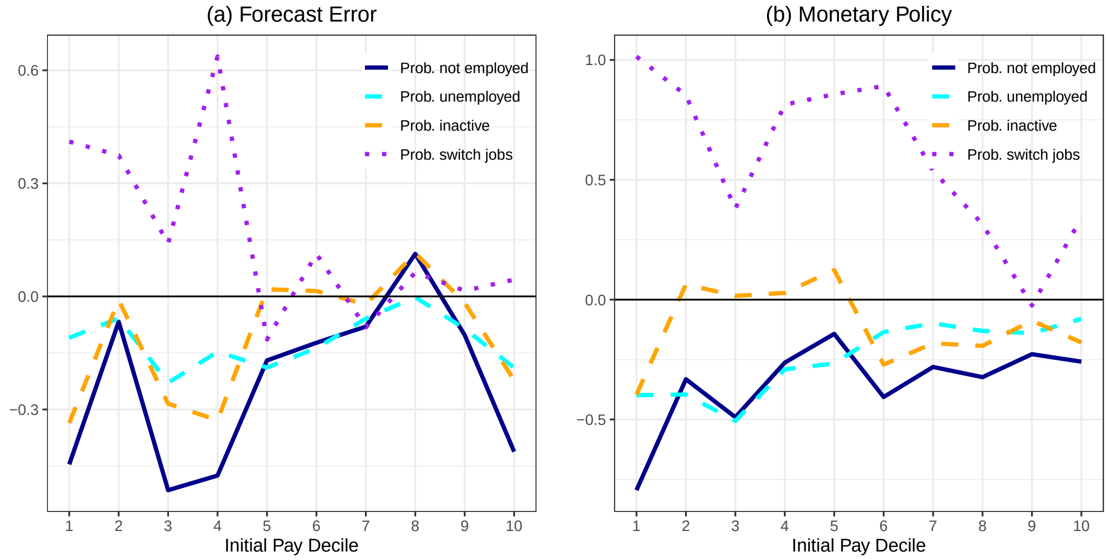
Notes: See notes for Figure 2. The coefficient estimates are the result of an instrumental variable strategy which uses GDP forecast errors from the VAR discussed in Appendix A.2 as an instrument for GDP growth.

Figure A.2.3: Pay Betas Decomposition - MP shocks



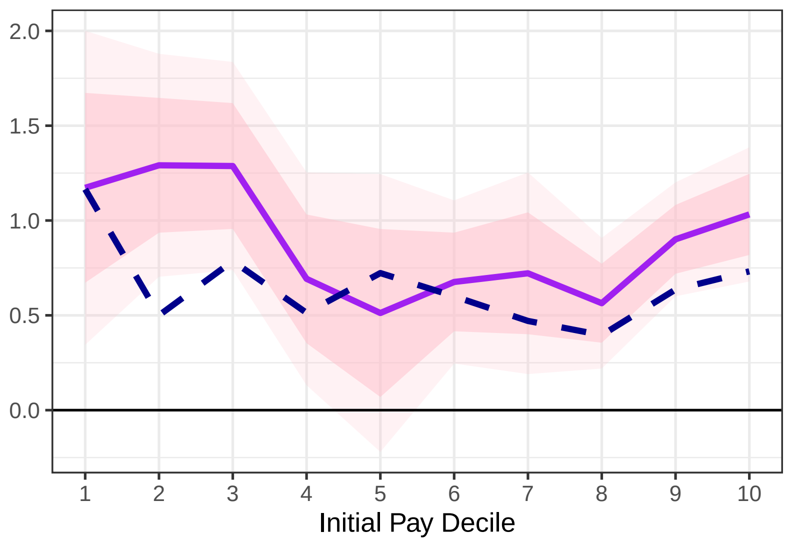
Notes: See notes for Figure 2. The coefficient estimates are the result of an instrumental variable strategy which uses accumulated high frequency monetary policy shocks as an instrument for GDP growth.

Figure A.2.4: Labour Market Transition Betas for Transitory Shocks



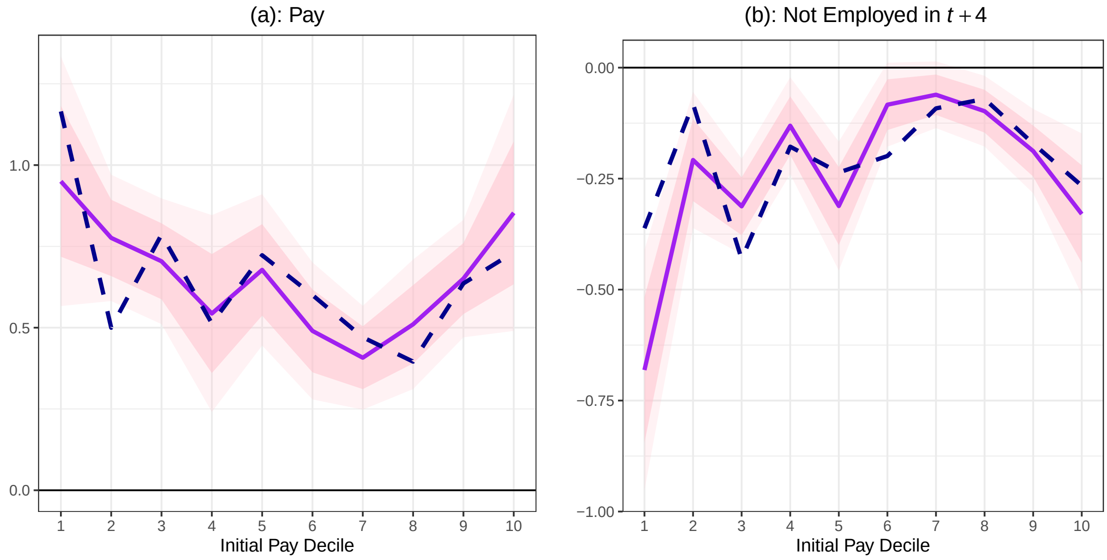
Notes: See notes for Figure 3. Panel (a) plots coefficient estimates that are the result of an instrumental variable strategy which uses GDP forecast errors from the VAR discussed in Appendix A.2 as an instrument for GDP growth. Panel (b) plots coefficient estimates that are the result of an instrumental variable strategy which uses accumulated high frequency monetary policy shocks as an instrument for GDP growth.

Figure A.3.1: Household Pay Beta



Note: The purple line plots the coefficients β_g from Equation (2) but aggregating and sorting 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.

Figure A.3.2: GDP Betas (excluding part-time workers in t)



Note: The purple line plots the coefficients β_g from Equation (2) but excluding part time workers in the initial period. 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.

part time employees are are shown in Figure A.3.2 and serve to underscore the conclusions from the previous sections. In particular the pay beta is slightly more U-shaped and the slope of the non-employment beta is steeper.

A.3.3 Recessions

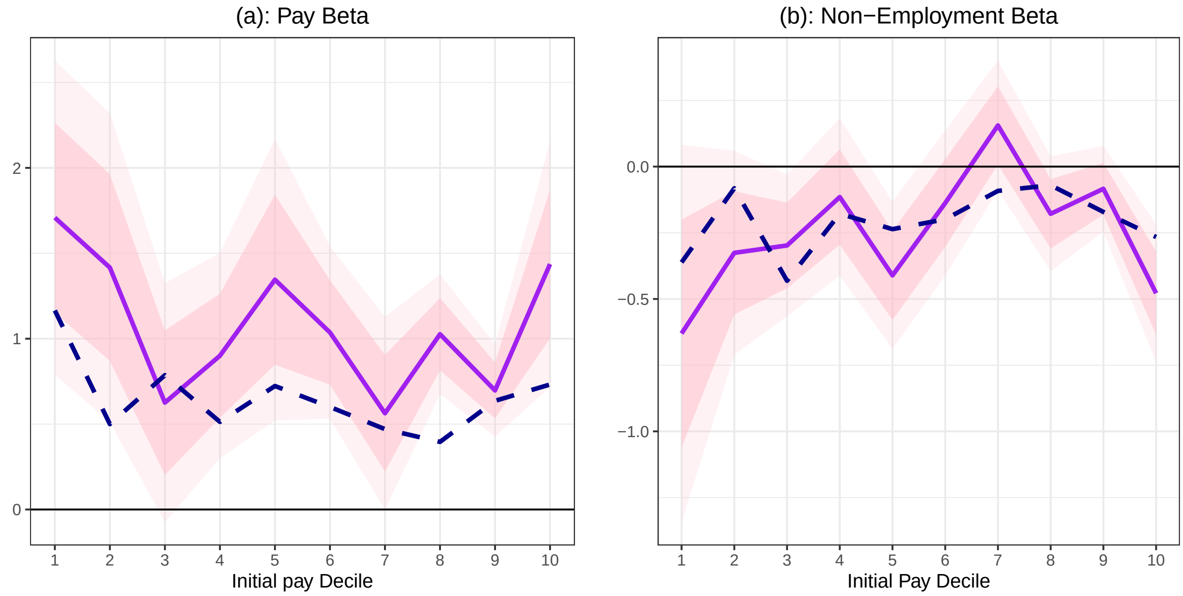
In this sub-section we asses whether controlling (discounting) for periods of negative growth and in particular the great recession effects our beta estimates. We do this by including indicators of negative growth between periods t and $t + 4$ as an interaction term with GDP growth in Equation (2). Figure 9 plots the estimated betas in purple after having included the interaction term. 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 pay betas excluding the impact of recessions are highest at the bottom and lowest in the upper middle. The estimated average beta across the distribution is higher as was found by Bell et al. (2022). This suggests real labour incomes are more sensitive to positive shocks than negative which is consistent with other findings of downward real and nominal rigidity.[16] Focusing on the extensive margin (panel (b)) the estimated profile is close to the whole sample estimate.

A.3.4 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. Figure A.3.4 plots the GDP betas for the change in the variance of pay growth for initially employed people by income decile. We see that pay variance betas are negative across the distribution, and slightly more so in the bottom half though this relationship is flatter than for actual pay. The reduction in variance while statically significant is, however, relatively small when compared to the average variances reported in most income deciles in Figure 1. The fact that the betas

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

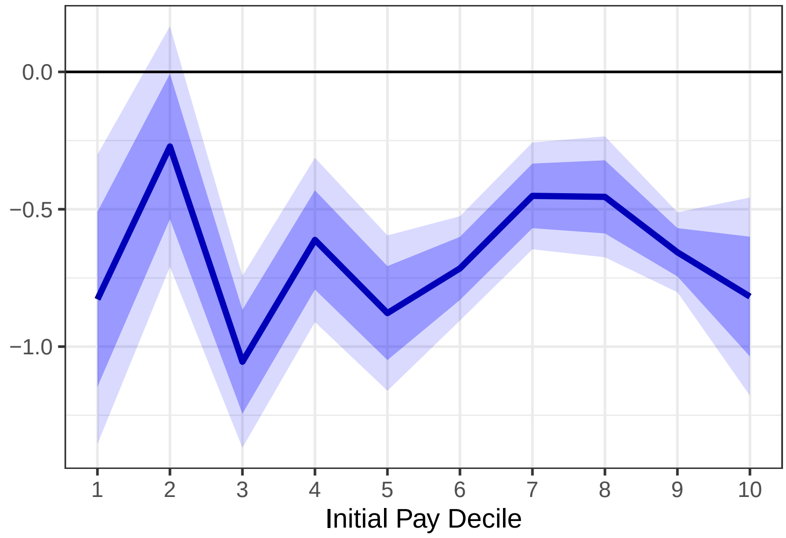
Figure A.3.3: Impact of Recessions on Betas



Note: 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.

for pay growth variance are negative can be explained by the negative correlation between extensive margin labour market transitions and GDP movements. A positive economic shock reduces the probability of becoming unemployed (Figure 3), which reduces variance in pay growth for the initially employed. The fact that the variance shift is quite flat and small across the distribution may be partially explained by the positive correlation between GDP movements and job switching (Figure 3), which pushes in the other direction for pay variance at the bottom of the income distribution.

Figure A.3.4: Pay Variance Betas



Note: Figure plots results for Equation (2) with pay variance $Var(dy_{t+4})$ on the LHS. 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.