The Impact of Aggregate Fluctuations Across the UK Income Distribution

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Abstract

In this paper, we examine 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 find that the sensitivity is largest at the very bottom of the income distribution, generally larger in the bottom half of the income distribution and lowest in the upper middle portion of the distribution. We present a decomposition of the impact on pay which indicates a significant role for transitions to unemployment in generating the overall results, with these extensive margin adjustments most important in the bottom half of the income distribution.

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1 Introduction

What is the incidence of fluctuations in aggregate economic activity across the income distribution? Whose income changes and who becomes unemployed? Are hours cut back or increased or is it movements into and out of unemployment that matter more?

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) the decomposition of changes in income into changes in employment, hours and pay; and (2) evidence from 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, where individuals remain in the survey for up to five quarters. We estimate pooled OLS regressions of changes in pay or labour market status on changes in Gross Domestic Product over the same period. We estimate regressions by initial pay decile and refer to the coefficients on changes in GDP as GDP betas. We show that these GDP betas can best be interpreted as elasticises to transitory fluctuations in GDP.

Overall we find pay betas to be largest at the very bottom of the income distribution, generally larger in the bottom half of the income distribution and lowest in the upper middle portion of the distribution.[1] Decomposing the overall pay betas indicates a significant role for movements into unemployment in driving the overall results, with extensive margins transitions most important in the bottom half of the distribution. In contrast, changes in real hourly pay are found to be the most important determinant in the upper middle portion of the income distribution. We also find 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 and GDP forecast errors. We are also able to compare our beta estimates to average unconditional (or steady state) transition rates across the income distribution. Unlike average labour market transition rates, which are largely explained by movements into and out of inactivity, movement into and out of unemployment explain the majority of the movements in labour market transitions rates related to the business cycle.

In further analysis we find that the overall pay betas are similar whether grouping at the individual or household level. Similarly, we don't find significant differences when controlling for negative GDP growth periods. We estimate a negative GDP beta for the variance of pay growth which follows from the positive correlation between GDP fluctuations and extensive labour market transitions that drive the difference in pay growth variance between groups across the income distribution.

Our results will be of interest to fiscal and monetary policy makers in helping inform them of the 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 such as McKay & Reis (2016).

1.1 Related Literature

As discussed this paper fits into a growing literature that seeks to understand the distributional implications for households and individuals of movements in the aggregate business cycle. Gu-

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

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

venen 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 households estimated as being 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. The conclusions from these papers vary but a common thread is that of excess sensitivity to business cycle fluctuations induced by monetary policy at the bottom and top of the distribution, with labour income most important at the bottom of the distribution and capital income more important for 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) further examine extensive margin adjustment. Hoffmann & Malacrino (2019) analyse administrative data from Italy to conclude that employment changes and spells of unemployment drive the pro-cyclical skewness of income. Broer et al. (2022) similarly find that the extensive margin is key to explaining the excess sensitivity to business cycle at the bottom of the distribution.

In terms of the UK, Bell et al. (2022) use the Annual Survey of Hours and Earnings to study earnings dynamics and inequality. They find that the variance of earnings has increased over time and that earnings exhibit pro-cyclical skewness. Cantore et al. (2022) study the effect of monetary policy in the US and UK on hours worked and unemployment across the distribution including in a pseudo-panel constructed from the LFS. The authors find an initial counter-cyclical response at the very bottom of the income distribution of hours worked conditional on a monetary policy shock, though this effect is not persistent into the peak transmission period in the case of the UK.

The rest of this paper is structured as follows. Section 2 described 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.

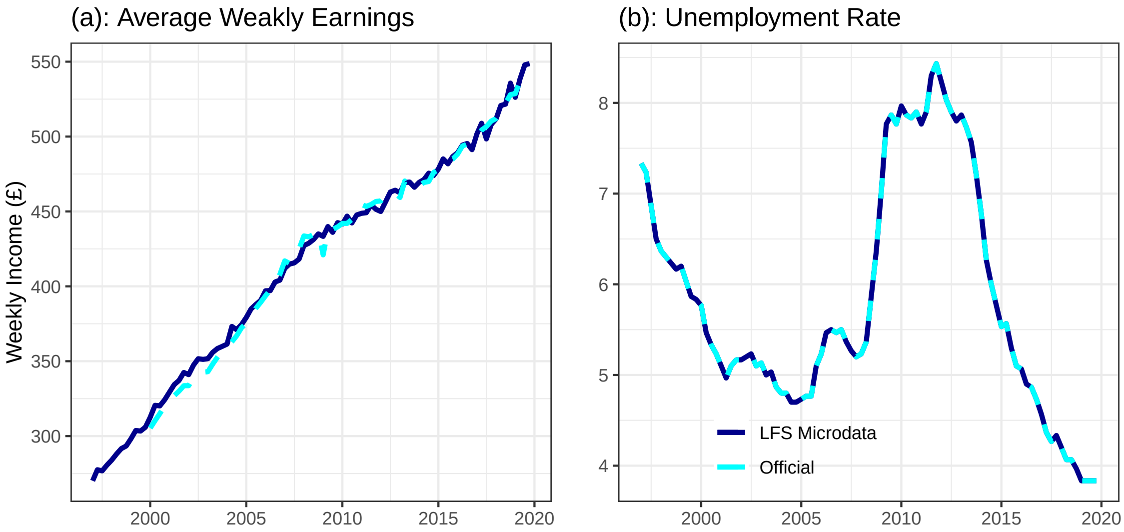
2 Data and Descriptive Statistics

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 underpins the UK's national labour market statistics including the official unemployment measure, and measures of labour force participation 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 selected households stay in the survey for five quarters (waves) to enable the analysis of labour market transitions. 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 income over a 1 year period for employed individuals. Participants are asked to report their pay for the interview week from their main and if applicable 2nd job. Alongside their current labour market status and recent employment history they also report on hours worked in their main job. The LFS measure of labour earnings, while not the official measure (AWE), tracks the official measure very closely (see Figure 1) and is the preferred source of pay for 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).

Figure 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 latest official AWE measure from ONS is available from January 2000.

2.1.1 Limitations

LFS unemployed and inactive members of the population 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 do not answer the income questions in the LFS and so this analysis also abstracts from this section of the labour force. Since the global 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, it is a sample and lacks the big data advantages of 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 cyclicality of labour earnings, hours and labour market transitions across the income distribution by estimating their elasticity with respect to GDP by income decile. Like Broer et al. (2022) we first group households by income decile and then take averages over each decile in current and future periods:

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

where g is an income group, i is an individual in the LFS, $t \in \{0, 4\}$, $w_{i,t}$ 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.[3]

[3]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

Table 1: Percentiles

(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) Hours

Period	1	2	3	4	5	6	7	8	9	10
(1996,2003]	13.5	23.5	33.3	37.5	39.2	40.5	41.4	41.6	41.5	43.0
(2003,2007]	14.2	23.9	33.2	37.1	38.7	39.6	40.4	40.6	40.7	41.8
(2007,2011]	14.5	23.6	32.6	36.5	38.2	39.0	39.8	40.0	40.2	41.4
(2011,2015]	14.8	24.1	32.4	36.6	38.0	39.1	39.5	39.9	40.2	41.3
(2015,2019]	15.5	24.9	32.7	37.0	38.4	39.2	39.8	40.1	40.3	40.9

Note: Nominal pre-tax average weekly earnings and hours worked by income percentile over grouped periods of employed individuals.

Average weekly earnings and hours worked by income decile are reported in Table 1. Table 1 shows that 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 that reported by the UK's tax authority (HMRC), which are closer to 25 and 5.5, respectively.[4] In terms of hours worked we see that hours are increasing with weekly income, though the differences in hours worked are small in the top half of the distribution. The lower values reported in the bottom deciles reflect a higher share of part-time and flexible workers in these buckets.

This study is also focused on individual labour market transitions. Figure 2 reports average transition rates between quarter t and $t + 4$ by income decile in quarter t.[5] 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 reflected in higher real pay growth variance at the bottom. Figure 3 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. The differences in pay growth variance is nearly completely explained by extensive margin transitions with the variance for those that remain employed in both periods nearly flat across the income distribution (orange dashed line).

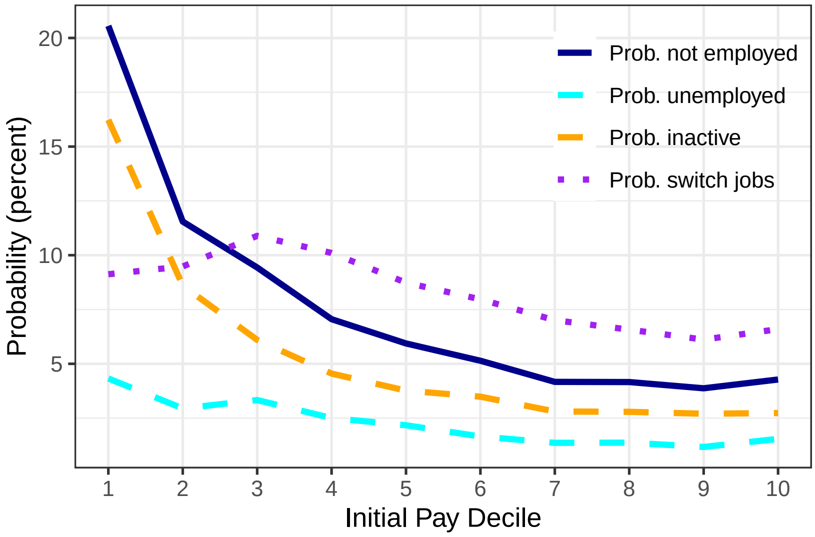
Finally, the value in being able to follow individuals as opposed to following using pseudo-panel data (e.g. Verbeek (1996)) is illustrated in Figure 4. Here we have calculated a transition matrix between income deciles and non-employment between periods t and $t + 4$. First, it is

based on initial income.

[4]HMRC Survey of Personal Incomes.

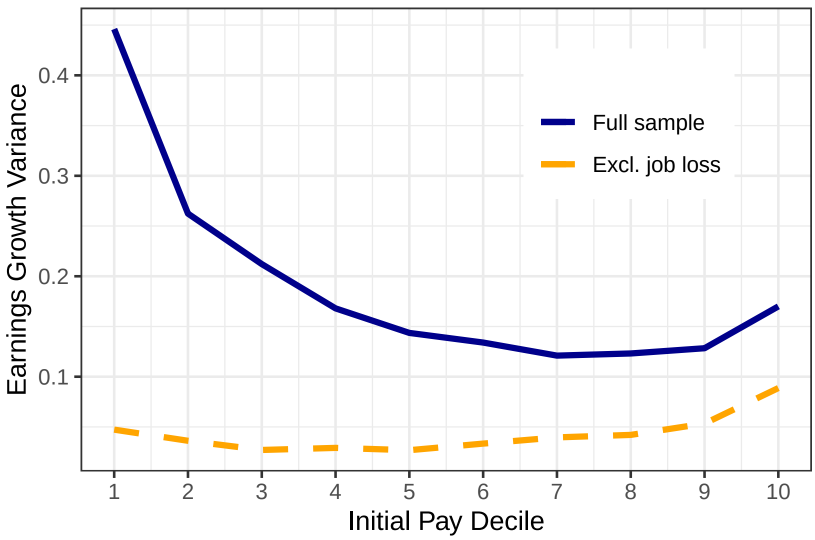
[5]Note that unlike our main results, these are averages unconditional on changes in GDP and so represent a mix of steady state and business cycle induced transitions.

Figure 2: Labour Market Status in $t + 4$.



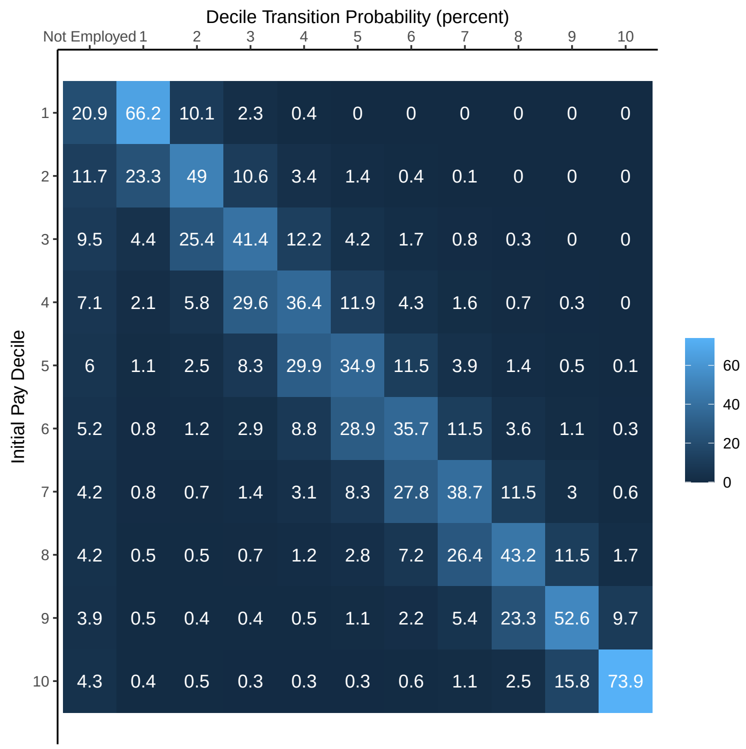
Note: Figure shows average labour market transition probabilities between t and $t + 4$. The red line shows the probability of leaving employment, the green line shows the probability of becoming unemployed, the blue line shows the probability of becoming inactive and the purple line shows the probability of changing employer. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

Figure 3: Earnings Growth Variance by Income Quantile.



Note: Figure plot the variance of earnings growth between period t and $t + 4$ across our sample period (1997Q2-2019Q4) by initial income decile. Individuals pay growth is weighted using the provided LFS survey weights.

Figure 4: Pay Decile Transition Matrix



Note: Figure reports the average transition probability over our sample of transitioning to each pay decile or non-employment over 4 quarters conditional on your pay decile in period t.

noteworthy (as is also shown in Figure 2) that transitions to non-employment frequently occur across the initial income distribution and this margin is either omitted or must be imputed in a pseudo-panel approach, where one cannot follow individuals from period to period. Second, in all but the lowest and highest income deciles the share remaining in that decile a year later is less than 50 percent.

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 probability of a transition to unemployment or inactivity; and or the probability of changing jobs.

Similar to Guvenen et al. (2017), our main GDP beta regressions is specified as follows:

$$y_{g,t,4} - y_{g,t,0} = \alpha_g + \beta_g \Delta GDP_{t+4} + \epsilon_{g,t} \tag{2}$$

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 movements. To see this consider individual wage growth determined 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 $dgdp_t = dg_t + da_t$, composed of a slow moving trend growth dg and faster moving business cycle component da. Individual pay can also change due to age and experience dL and due to individual idiosyncratic changes dz. If we then estimate the regression:

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

we will yield 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've 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) as 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 GDP growth is determined by shorter run business cycle movements, as suggested by analysis for UK such as in 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 the constant α_g as largely picking 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 described above, we also estimate GDP betas by trying to isolate more transitory business cycle frequency movements in GDP. We do so by estimating equation 2 via two stage least squares, instrumenting for changes in GDP with either accumulated monetary policy shocks prior to time t or the unexpected component of GDP growth between period t and $t+4$.[6] Both methods draw upon a six variable VAR as detailed in Appendix A.2, with the first stage explaining a significant share of movements in GDP as indicated in Table 2.

4 Results

4.1 GDP Betas

Figure 5 plots our main estimate of β_g from equation 2 for pay growth between period t and $t + 4$. Despite some volatility at the bottom, the overall picture suggests a mildly downward sloping GDP beta estimate as we move across the distribution from the lowest income groups to the higher incomes groups, with a small reversal as we move past the lowest variance income groups (deciles 7 and 8).[7] The overall average beta is around 0.6, which is fairly close to the estimates in Bell et al. (2022) using a longer sample of UK earnings data.

Figure 6 further decomposes the GDP beta estimates across the income distribution. Panel (a) compares the point estimate from Figure 5 in dark blue to the results from two subsamples. The orange dashed line shows the point estimate only for those that remain employed

[6] 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.

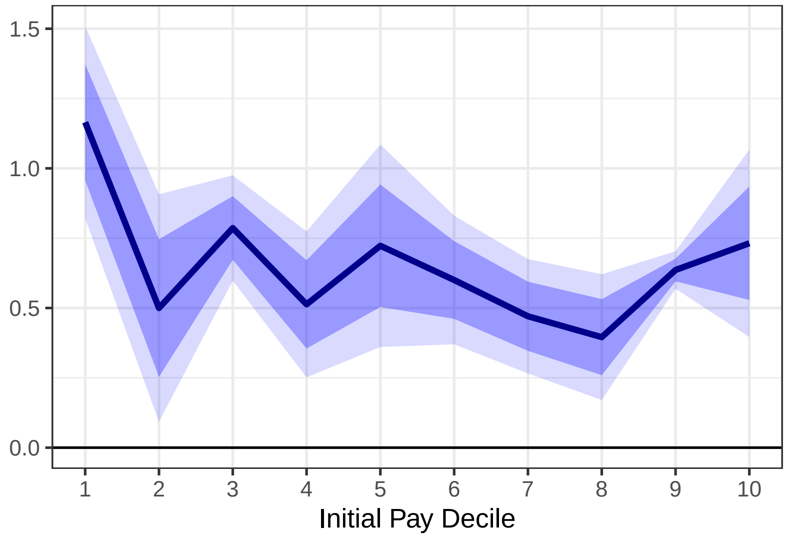
[7] See Figure 3.

Table 2: 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

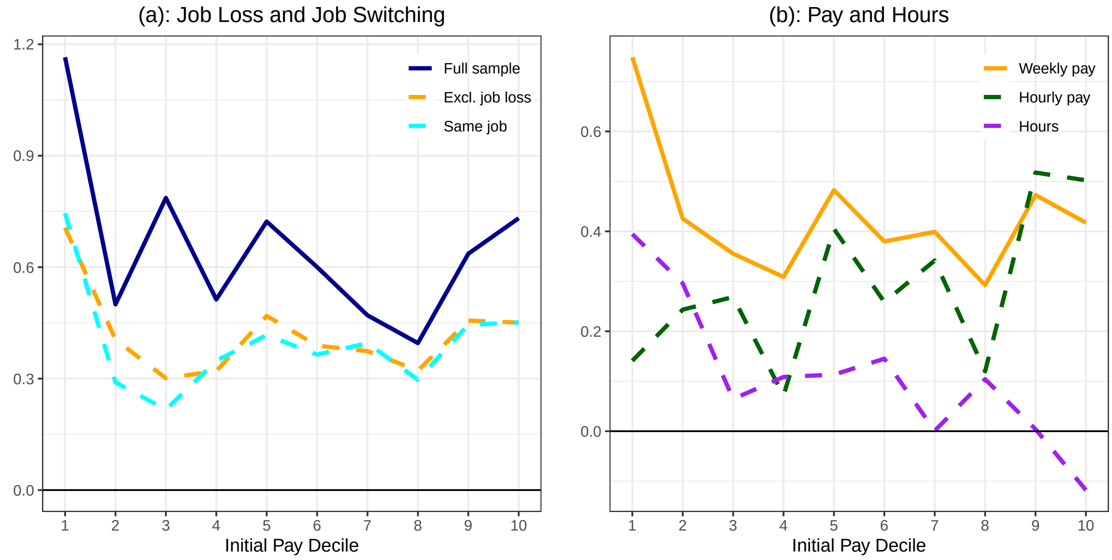
Note: Table shows results from first stage regression $\Delta GDP_{t+4} = z_t + \epsilon_t$. In the monetary policy shock implementation z is accumulated high frequency shocks from one (quarters $t-1$ to $t-4$) and two years prior (quarters $t-5$ to $t-8$). In the forecast error version z is the 1 year 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.

Figure 5: Pay Beta by Decile



Note: The blue line plots the coefficients β_g from Equation 2. 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.

Figure 6: Pay Betas Decomposition



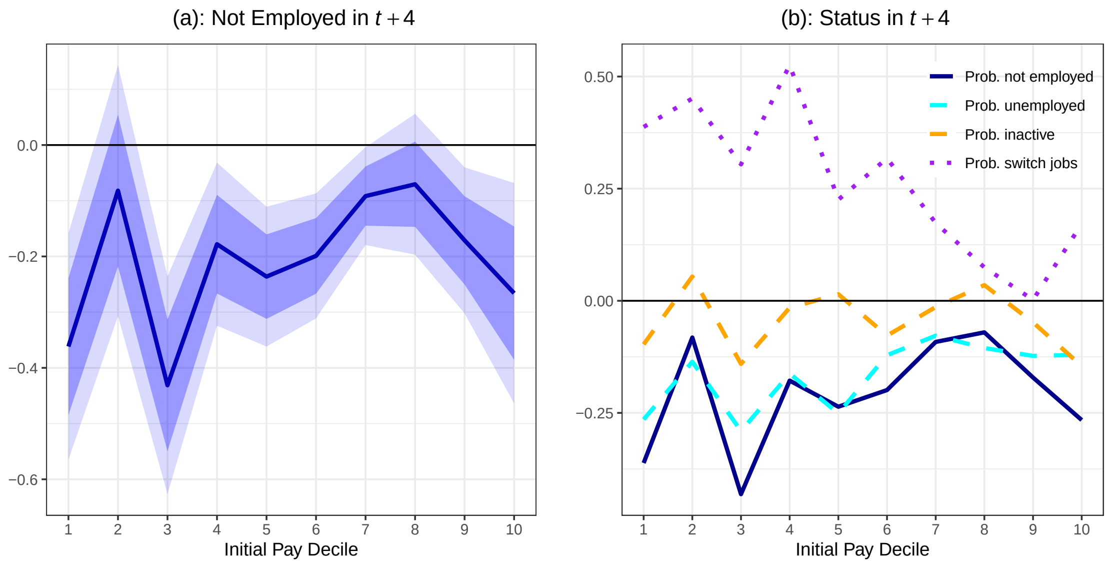
Note: Panel (a) plots the coefficients β_g from Equation 2 for different samples: the blue line plots the coefficients for the full sample, as in the blue line in Figure 5; the orange dashed line plots the coefficients for those individuals that remain employed in $t+4$; the cyan line plots the coefficients for those individuals that remain with the same employer in $t+4$. Panel (b) 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 (a); 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 period t and $t+4$. The estimated betas for those that remain employed is uniformly below the whole sample estimates and by some margin for certain income deciles. This implies an important role for the extensive margin in determining GDP betas across the distribution, particularly so at the bottom and top. The dashed cyan line in panel (a) further restricts the sample to those that stay in the same job but is not significantly different from the orange line suggesting that job switching is not a large driver of the GDP betas. Panel (b) focuses on those that remain employed (the orange line) and approximately decomposes the GDP beta point estimate into changes in hourly pay and changes in hours. 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; explaining 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.

Figure 6 panel (a) implies an important role for the extensive margin in determining the sensitivity of incomes across the UK income distribution, and Figure 7 focuses on this margin 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 $t+4$. Overall, a 1 percent change in GDP is associated with around a 0.2 percentage point reduction in moving to non-employment. With the exception of decile 2, the negative non-employment GDP betas are larger in the bottom half of the distribution and smallest at the lowest variance points of the income distribution before becoming more negative again at the very top.[8]

[8] It's difficult to tell whether the decile 2 estimates reflect genuine differences or just sampling volatility. Cantore et al. (2022) et al find some evidence of countercyclicality of labour supply at the very bottom which could be consistent with the response. Average hours worked in decile 1 are much lower than in other buckets

Figure 7: 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. Panel (b) plots the coefficients β_g from Equation 2 using different dependent variables: the blue line plots the coefficients using the probability of non-employment as the dependent variable, as in the blue line 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; 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.

Panel (b) further breaks down 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 increase in extensive margins transitions resulting from GDP fluctuations. This is in contrast to the steady state or average transition probabilities shown in Figure 2 where the majority of movements into non-employment are explained by movements into inactivity. Finally, in Figure 7 we note that the GDP betas for job switching are downward sloping across the income distribution, more so than the average transition rate (Figure 2).

4.2 Transitory Shocks

As discussed in section 3 (equation 6), 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 like fluctuations by using GDP forecast errors and monetary policy shocks as first stage instruments for GDP growth as outlined in table 2. The key results are shown in Figure 8. The first row shows the results for the forecast errors approach. The pattern and magnitudes for the forecast errors approach are overall quite similar to that of the unconditional beta results for the previous sections. The pay beta (panel (a)) is higher 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. As in the unconditional case, the extensive margin again plays an important role in dictating this pattern (panel (b)).

which could reflect more marginally attached workers residing in this income group than in decile 2.

The bottom row of Figure 8 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 further results in Appendix A.3, the overall message of the conditional approach is similar to that of the unconditional approach as hypothesised in section 3.

4.3 Other Exercises

4.3.1 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.[9] 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 9 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.

4.3.2 Recessions

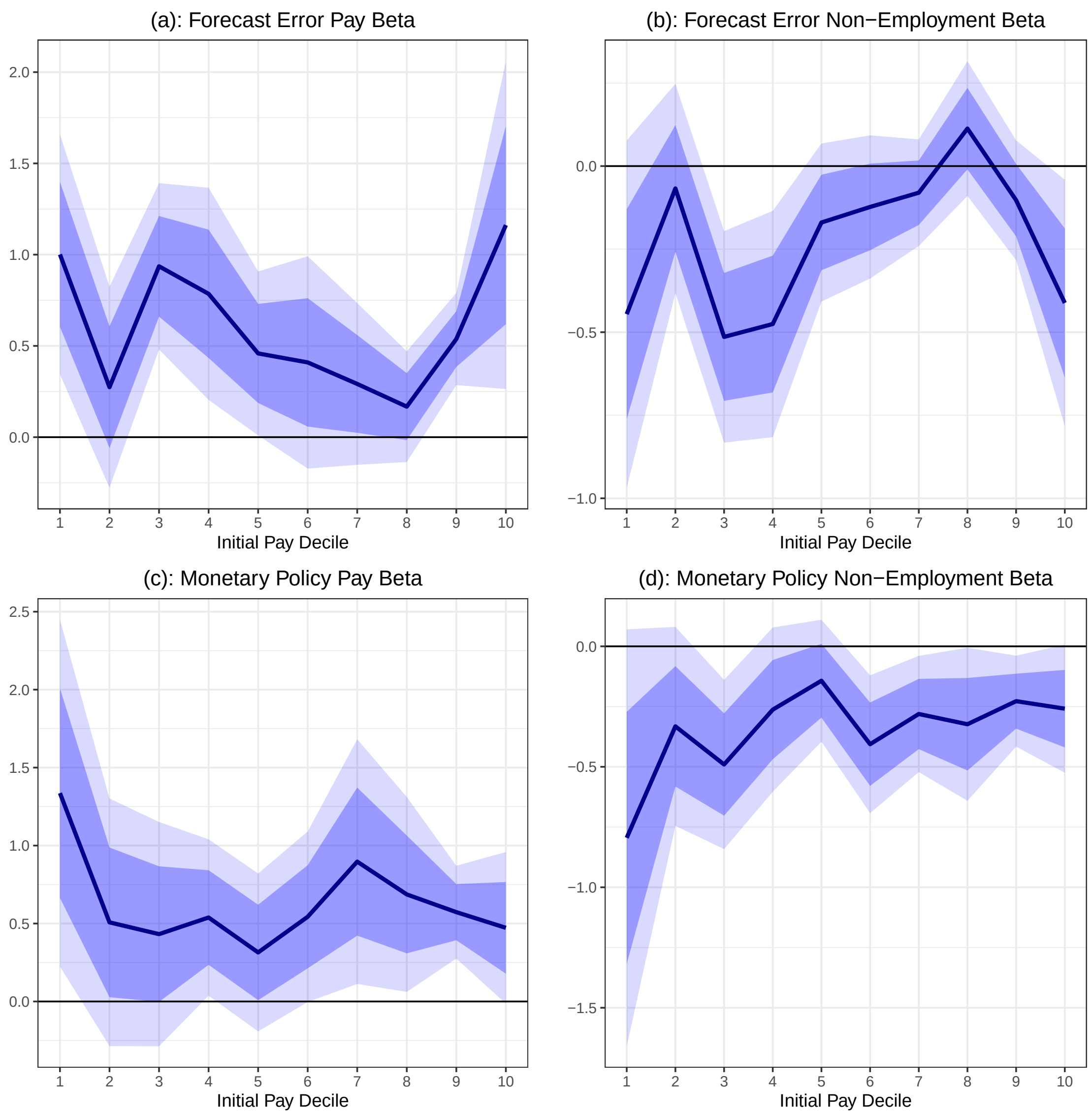
In this sub-section we asses whether controlling for periods of negative growth affects our beta estimates. We do this by including indicators of negative growth between periods t and $t+4$ as an interaction term with GDP growth in equation 2. Figure 9 plots the estimated betas in purple after having included the interaction term. The point estimates from Figure 5 and Figure 7 panel (a) are included as the blue dashed lines for comparison. Overall we see that the pay betas estimated 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.[10] Focusing on the extensive margin (panel (b)) the estimated profile is close to the whole sample estimate.

4.3.3 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 11 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 3. The fact that the betas 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

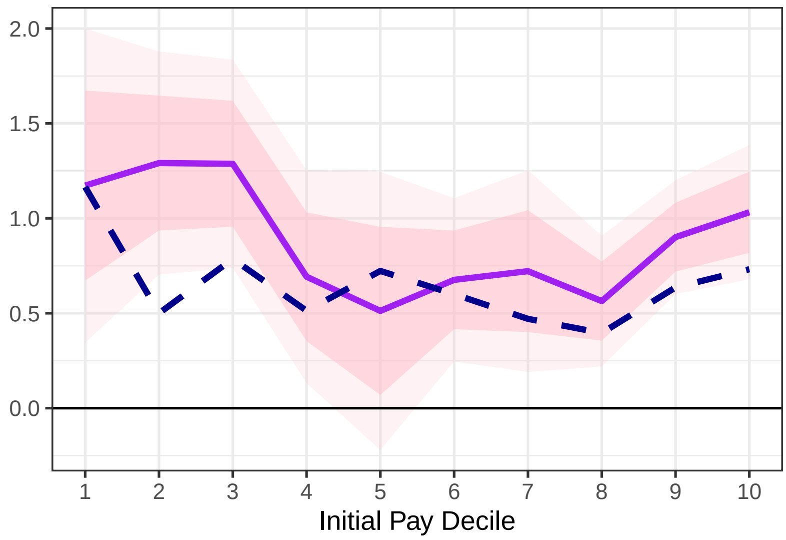
[9]The majority of the related literature has conducted its analysis at the individual level.
[10]See Grigsby et al. (2021) and references therein.

Figure 8: Betas for Transitory Shocks



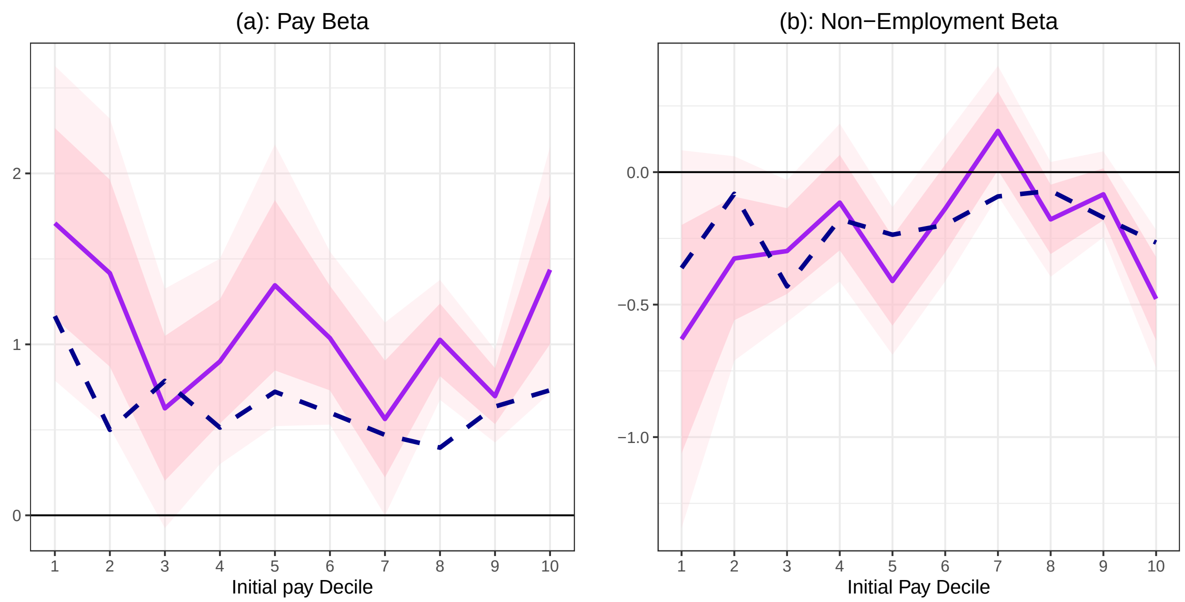
Note: Panel (a) and panel (b) plots the coefficients from equation 2 under an instrumental variable approach using GDP forecast errors from the VAR discussed in Appendix A.2 as an instrument for GDP growth. Panel (c) and (d) follows the same procedure but uses accumulated high frequency monetary policy shocks. The darker (lighter) shaded area represents the 68% (90%) confidence interval. HAC standard errors reported. Individuals are sorted into deciles in each quarter based on their earnings in t. The sample period is 1997Q2-2019Q4.

Figure 9: Household Pay Beta



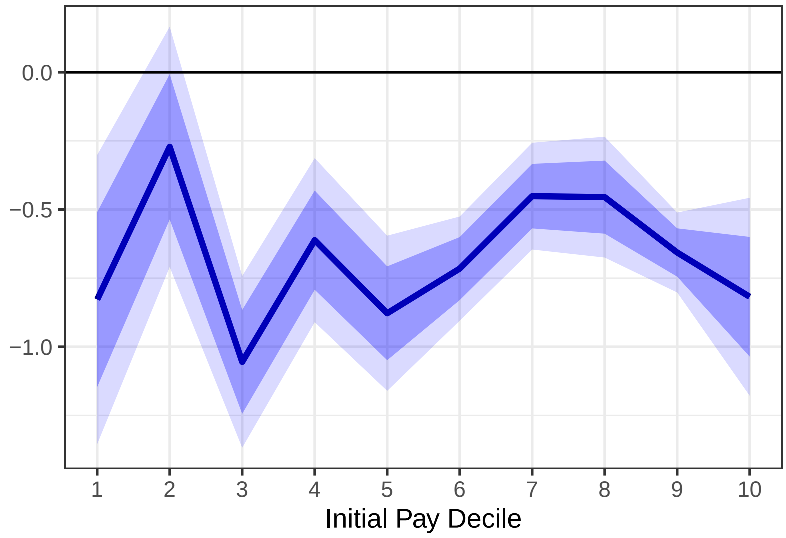
Note: The purple line plots the coefficients β_g from Equation 2 but aggregating and sorting at the household level rather than the individual level. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. Households are sorted into deciles in each quarter based on household earnings in t. The blue dashed line repeats the estimate from Figure 5. The sample period is 1997Q2-2019Q4. HAC standard errors reported.

Figure 10: 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.

Figure 11: 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.

of becoming unemployed (Figure 7), 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 7), which pushes in the other direction for pay variance at the bottom of the income distribution.

5 Conclusion

This paper has presented empirical results on the sensitivity of pay and labour market transitions to aggregate fluctuations in economic activity using the UK's Labour Force Survey. We have provided evidence that aggregate fluctuations have heterogeneous impacts across the income distribution, with greater sensitivity present at the bottom of the distribution largely driven by increased movements into and out of employment along the unemployment margin.

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

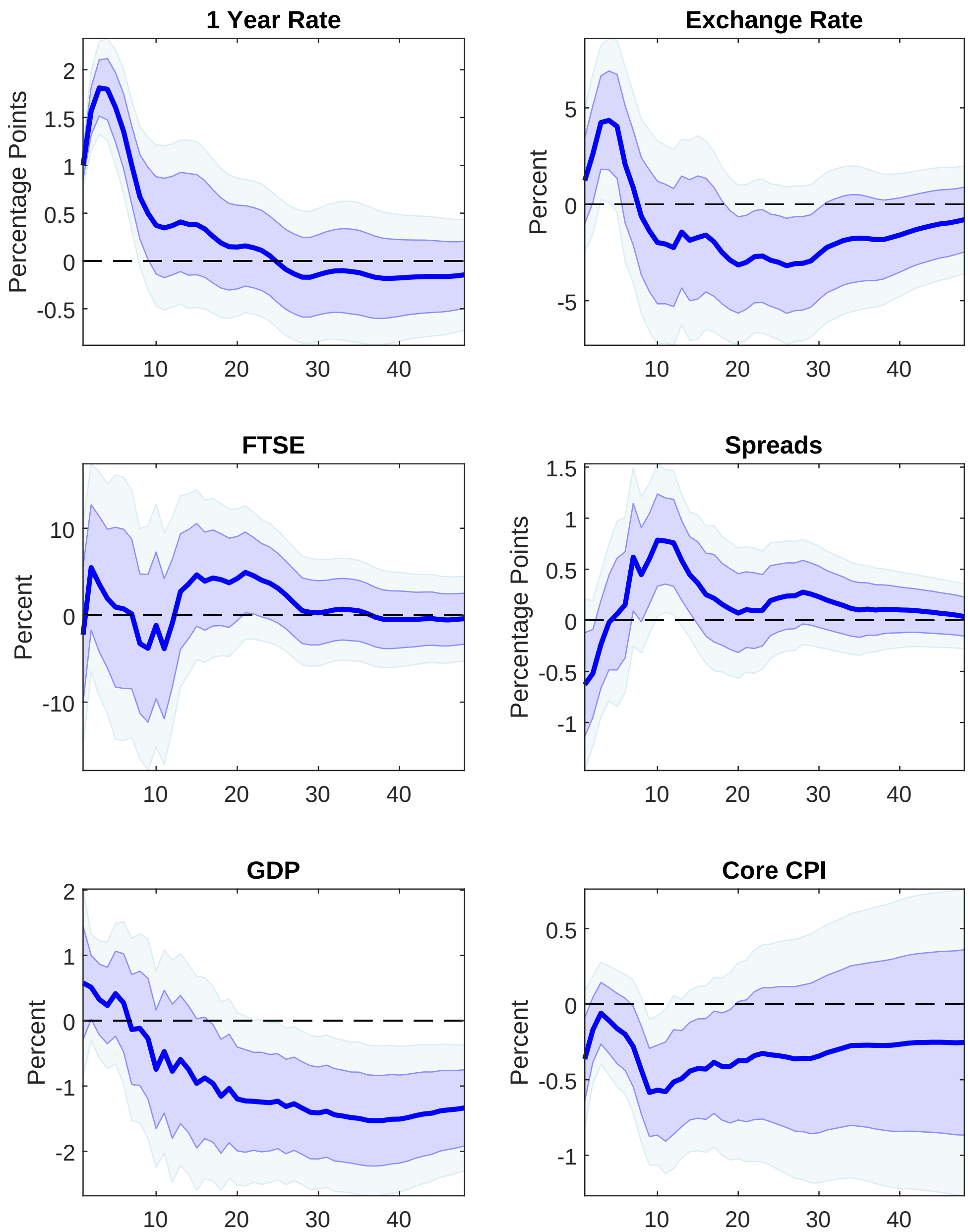
- **GDP**

  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 (see previous section).

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



Note: Figure shows impulse response normalised to a 1 percent monetary policy shock. Standard errors are derived using a moving block bootstrap (Jentsch & Lunsford 2022) with centered confidence interval reported in blue for the 68 and 90 percent windows.

A.2 SVAR

The SVAR described below supports the conditional beta 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.

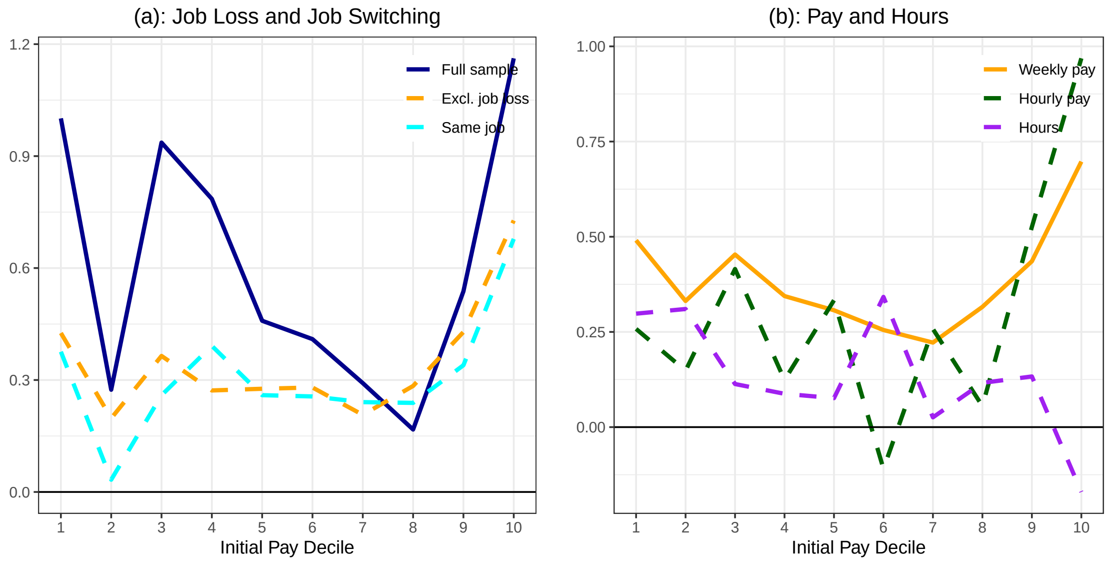
The VAR is estimated using monthly observations from 1996 to 2019 and 12 lags. The effect of monetary policy is identified using the external (proxy) instruments approach (Stock & Watson 2018). The instrument for monetary policy shocks is taken as the change in the price of sterling futures contracts 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.

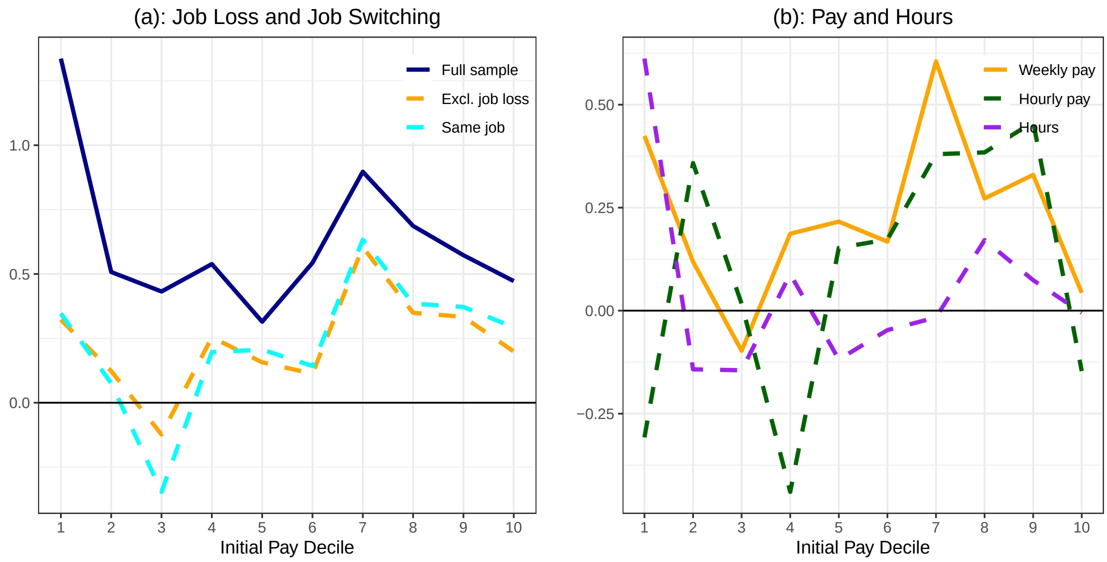
A.3 Additional results

Figure A.3.1: Pay Betas Decomposition - Forecast Errors



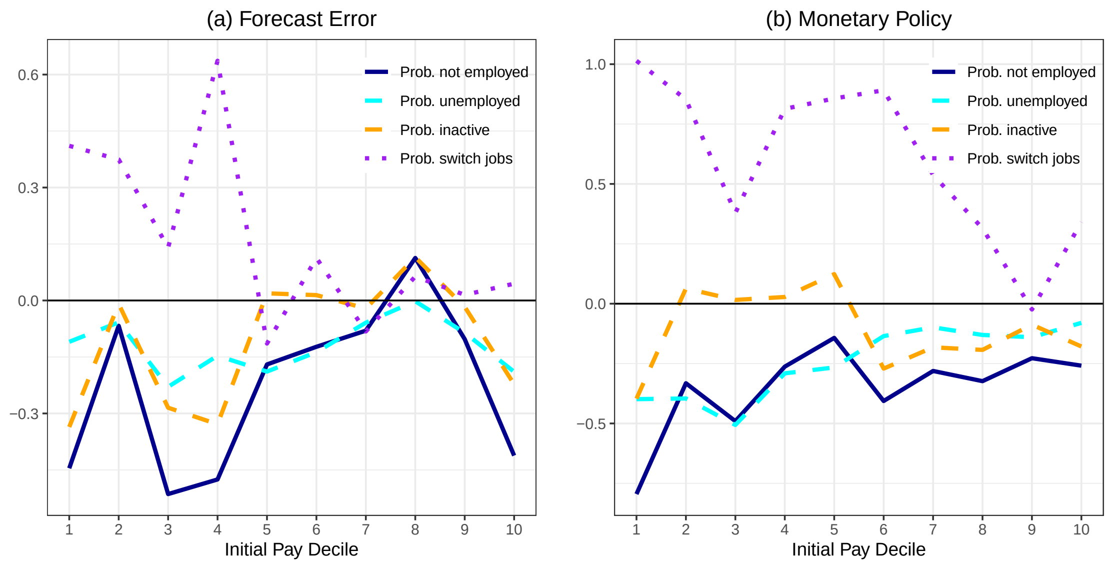
Notes: See notes for Figure 6. The coefficient estimates are the result of an instrumental variable strategy which uses GDP forecast errors from the VAR discussed in Appendix A.2 as an instrument for GDP growth.

Figure A.3.2: Pay Betas Decomposition - MP shocks



Notes: See notes for Figure 6. 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.3.3: Labour Market Transition Betas for Transitory Shocks



Notes: See notes for Figure 7. 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.