GDP Betas in the UK

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Abstract

This paper presents empirical results on the sensitivity of pay and labour market transitions to aggregate fluctuations in economic activity using the UK's Labour Force Survey. What we call GDP betas. 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. Decomposing the overall pay betas indicates a significant role for movements to unemployment in driving the overall results, with these extensive margins transitions most important in the bottom half of the distribution.

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1 Introduction

What is the incidence of aggregate fluctuations in economic activity across the income distribution? Who's 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 sought to answer these questions empirically e.g. 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), by looking at evidence from the UK economy. We do so using microdata from the UK's Labour Force Survey (LFS) which is the largest individual/household survey in the UK and underpins the UK's national statistics on employment. Our empirical approach is simple and takes advantage of the short panel element of the LFS where individuals remain in the survey for 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 the GDP betas. We show that these GDP betas can best be interpreted as elasticises to temporary fluctuations in GDP.

Overall we find pay[1] 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. 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 were the most important determinant in the upper middle portion of the income distribution. We also find GDP fluctuations were positively correlated with job switching in the bottom half of the distribution. These broad descriptions held for general fluctuations in GDP as well as fluctuations identified on 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 our overall pay betas to be 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[2] in helping inform them of the implications of any policy changes that may impact the aggregate business cycle. 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) or 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 the extensive employment margin. 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 paper finds 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.

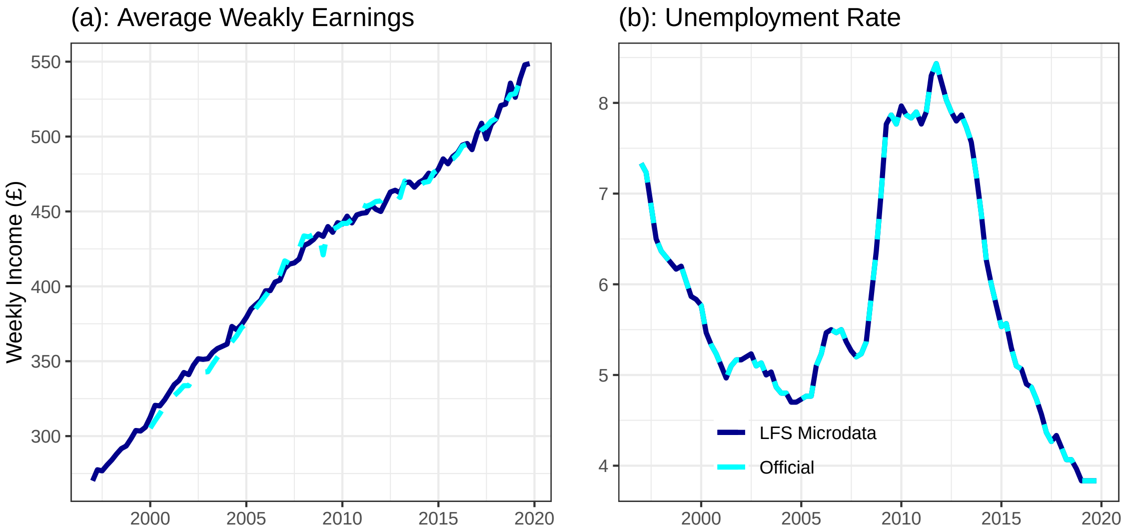
2 Data and Descriptive Statistics

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 employment statistics including the official unemployment measure, and measures of labour force participation and hours worked. The survey is 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 further asked to report their pre-tax labour earnings in 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 (see 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 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 provision of accurate survey weights. This underscores are decision to end our sample in 2019Q4. Finally while the LFS is a large nationally significant survey it is still only a sample and lacks the big data advantages of other 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 no finer than at the income decile level.

2.2 Descriptive Statistics

Our analysis focuses on the cyclicality of labour earnings, hours and labour market transitions over the income distribution by estimating their elasticity with respect to GDP by income decile. Like Broer et al. (2022) we first group[3] 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] In the 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 current income.

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 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 what is reported by HMRC[4] which are closer to 25 and 5.5 respectively. In terms of hours worked we see that hours are increasing in income though the differences in hours worked is small in the top half of the distribution. The lower values reported in the bottom deciles reflects 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[5] transition rates between quarter t and $t+4$ by income decile in quarter t. We see that typical labour market transition rates on average are close to monotonically decreasing in income. The probability of transitioning away from employment (blue line) is highest at the bottom distribution, and almost four times higher than at the top of the distribution. Typically most (around $\frac{3}{4}$) of transitions are into inactivity (orange line) with the remainder explained by transitions into unemployment (cyan line). Those at the bottom are also more likely to switch jobs (purple line) than those at the top.

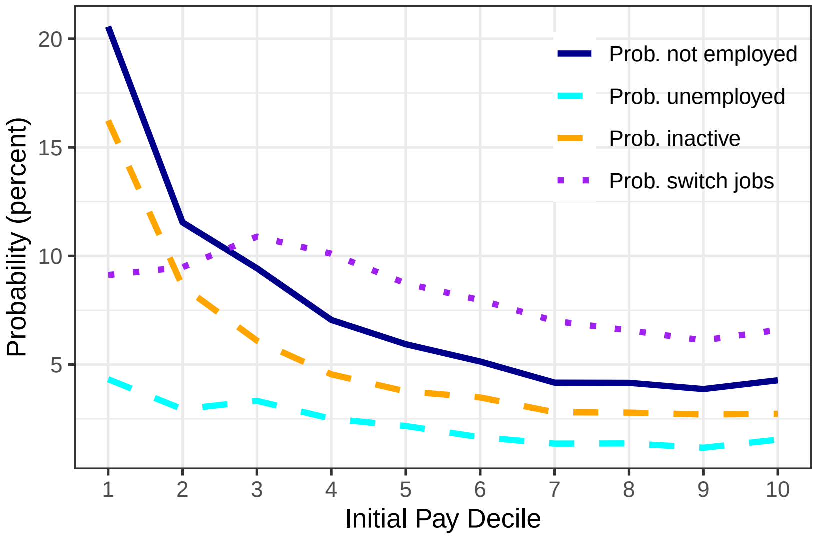
The propensity for more frequent labour market transitions at the bottom of the distribution is reflected in higher real pay growth variance. Figure 3 plots average pay growth variance by initial income decile which takes the form of an incomplete U shape with variance highest at the bottom and lowest in the upper middle deciles 7 and 8.

Finally the value in being able to follow individuals as opposed to following a pseudo-panel approach (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 $t+4$. Firstly it is 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. Secondly

[4]HMRC Survey of Personal Incomes.

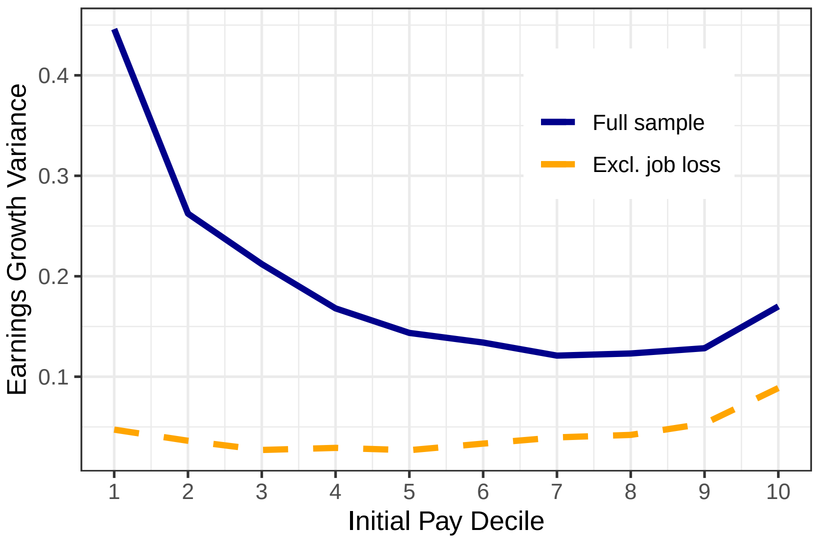
[5]Note that unlike our main results these are averages unconditional on movement in GDP and so represent a mix of steady state and business cycle elasticises.

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



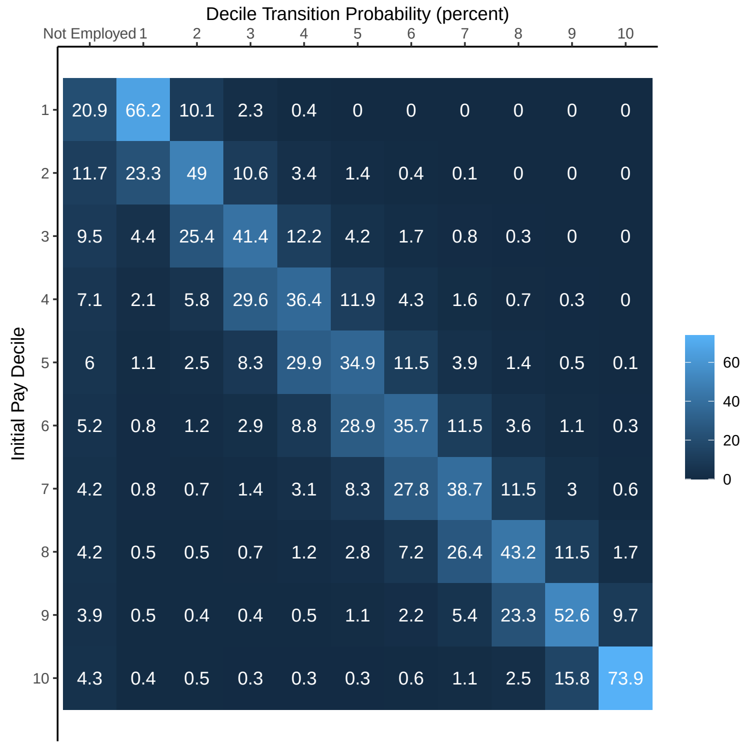
Note: Figure shows average labour market transition probabilities between t and $t + 4$. The red line shows the probability of leaving employment, the green line shows the probability of becoming unemployed, the blue line shows the probability of becoming inactive and the purple line shows the probability 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.

in all but the lowest and highest income deciles the share remaining in that decile is less than 50 percent.

3 Empirical Framework

Our empirical approach is simple and follows the example of other similar work e.g. Guvenen et al. (2017) or Broer et al. (2022) by running regressions of annual changes by income decile on aggregate changes in GDP. The elasticity β_g resulting from these regression we refer to as a GDP Beta. In terms of outcomes by decile we focus on labour income growth (log difference), hours growth (log difference), the linear probability of employment/unemployment /inactivity or the linear probability of changing jobs.

Similar to that of 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 slow moving trend growth and the elasticity to tempoary busieness 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

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 A1. HAC standard errors reported: *p<0.1; **p<0.05; ***p<0.01.

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:

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

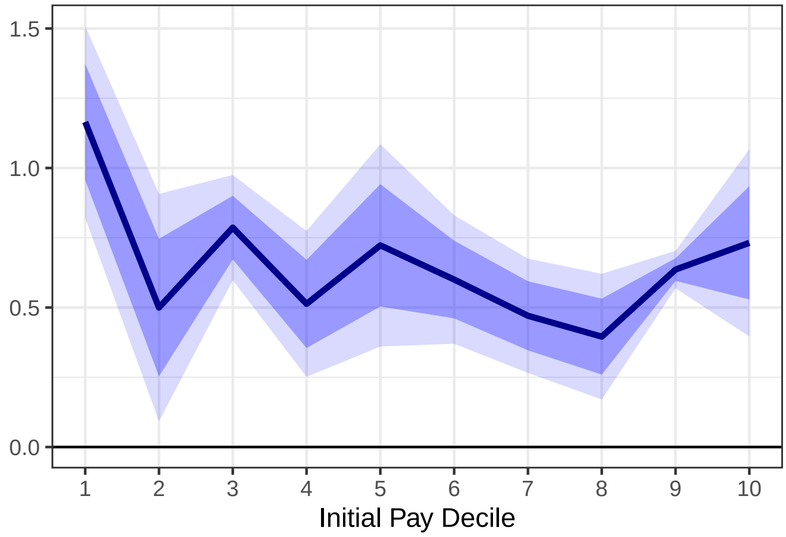
$$\beta = \frac{Var(dg)}{Var(dgdp)}\gamma_1 + \frac{Var(da)}{Var(dgdp)}\gamma_2 \tag{6}$$

Where we've assumed $E[da] = 0$ and $E[dadg] = 0$, i.e. temporary 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 temporary 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.

Alongside our main beta analysis we also estimate GDP betas by trying to isolate more temporary 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[6] prior to time t or the unexpected component of GDP growth between period t and $t+4$. Both methods draw upon a six variable VAR as detailed in appendix A2 with the first stage explaining a significant share of movements in GDP as indicated in Table 2.

[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 appendix A2.

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.

4 Results

4.1 GDP Betas

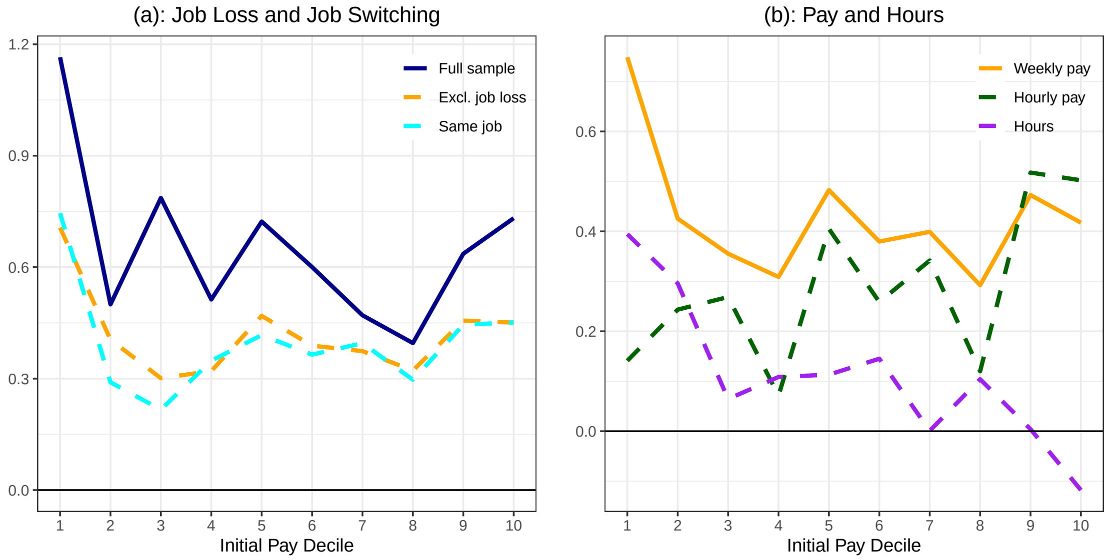
Figure 5 plot our main estimate of β_g from equation 2 for pay growth between period t and $t+4$. Despite some volatility at the bottom, the overall picture suggests a mildly downward sloping GDP beta estimate as we move along the distribution from the lowest income groups to the higher incomes groups,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

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 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 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 its 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 transition indicators as the LHS variable in equation 2. Panel (a) plots the

[7]See Figure 3.

Figure 6: Pay Betas Decomposition



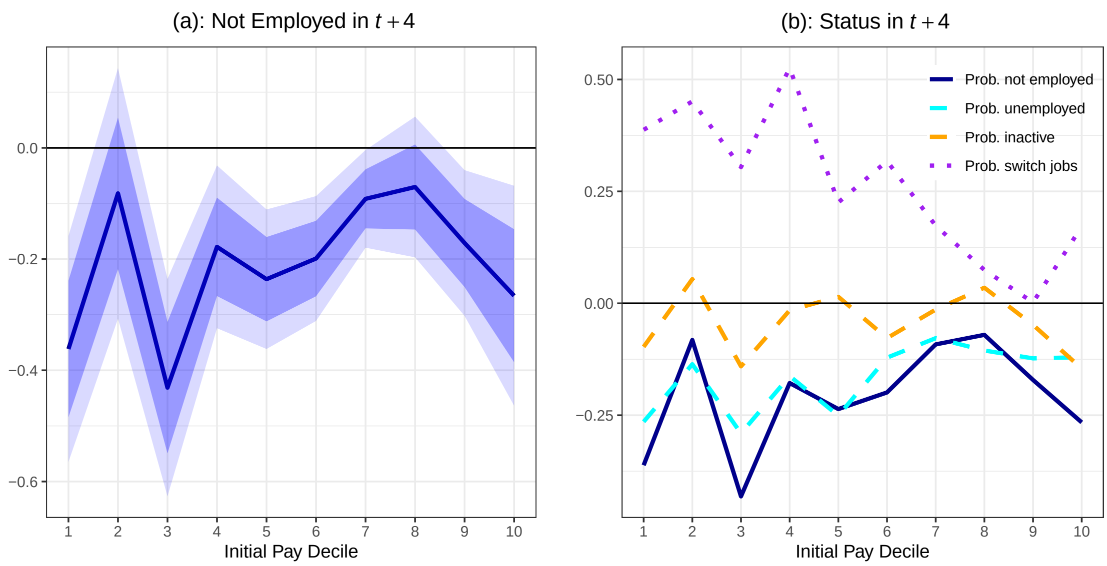
Note: Panel (a) plots the coefficients β_g from Equation 2 for different samples: the blue line plots the coefficients for the full sample, as in the blue line in Figure 5; the orange dashed line plots the coefficients for those individuals that remain employed in $t+4$; the cyan line plots the coefficients 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 red 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.

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[8] 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 become more negative again at the very top.

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).

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

Figure 7: Labour Market Transition Betas



Note: Panel (a) plots the coefficients from regressions with the probability of non-employment as the dependent variable. The solid black line plots the coefficients β_g from Equation 2. The darker (lighter) shaded area represents the 68% (90%) confidence intervals. The dashed blue line plots ... [might be easier if we have an equation to reference - with β_g^{IV} or something]. Panel (b) plots the coefficients β_g from Equation 2 with different dependent variables: the red line plots the coefficients using the probability of non-employment as the dependent variable, as in the black line in panel(a); the green line plots the coefficients using the probability of unemployment as the dependent variable; the blue 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.

4.2 Temporary Shocks

As discussed in section 3 (equation 6) the betas captured in the previous sub-section reflect a variance weighted average of trend growth (dg) and more temporary business cycle movements in GDP around trend (da). In this sub-section we try to isolate those more temporary 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)).

The bottom row of Figure 8 shows the results for monetary policy shocks. While still elevated at the bottom the pay beta point estimates in panel (c) is 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 ins the bottom half of the distribution. Taken together with further results in appendix A3, the overall message of the conditional approach is similar to that of the unconditional approach as hypothesized in section 3.

4.3 Other Exercises

4.3.1 Household Pay

While principally an individual 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 be effected by household considerations e.g. lower labour supply by one member may be compensated 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 line (deciles 2 and 3) pushes in the direction of greater sensitivity at the bottom of the distribution relative to the upper middle.

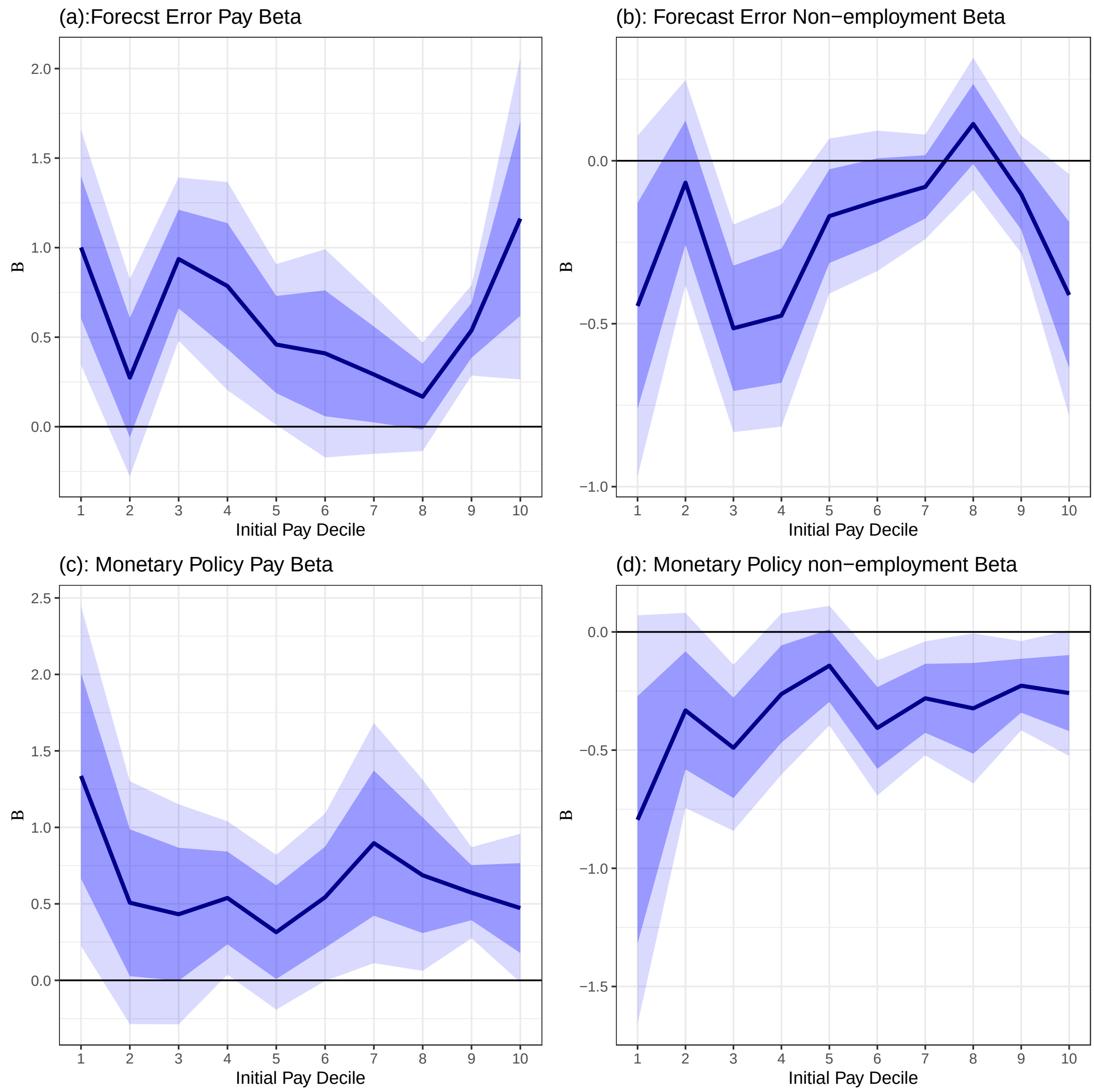
4.3.2 Recessions

In this sub-section we asses whether controlling for periods of negative growth 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 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].

[9]The majority of the related literature has conducted it's analysis at the individual level.

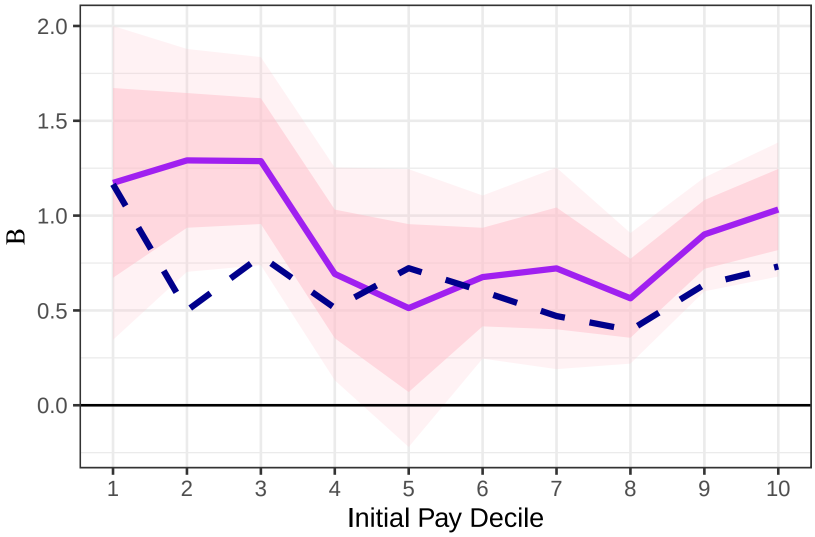
[10]See Grigsby et al. (2021) and references therein.

Figure 8: Betas for Conditional/Temporary 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 A2 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.

Focusing on the extensive margin (panel (b)) the estimated profile is close to the whole sample estimate.

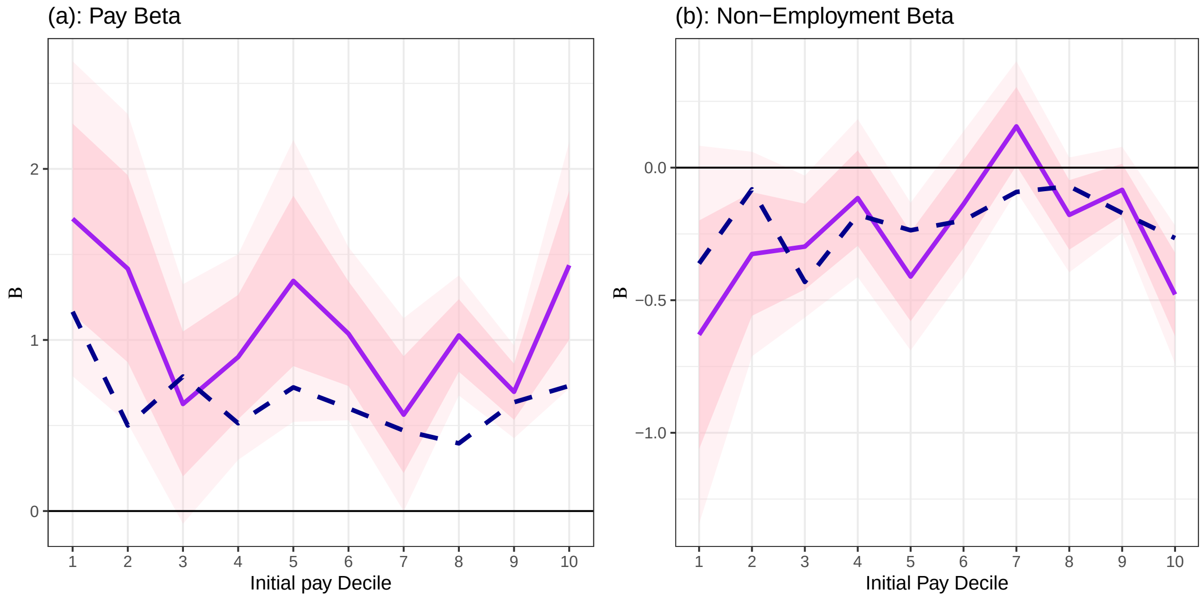
4.3.3 Income Variance

The change in variance of income growth across the distribution is a further object of interest and a theoretically important determinant of household consumption (Blundell & Preston (1998)). Figure 11 plot 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 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 of becoming unemployed (Figure 7) which reduces variance in pay growth for the initially employed. The fact 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

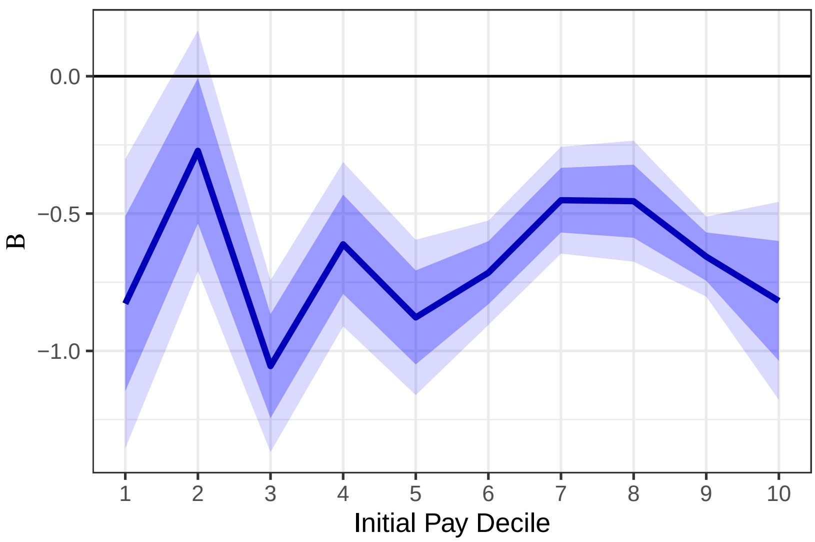
This paper has presented empirical results on the sensitivity of pay and labour market transitions to aggregate fluctuations in economic activity using the UK's Labour Force Survey. We have provided evidence that aggregate fluctuations have heterogeneous impacts across the income distribution with greater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

Figure 10: Impact of Recessions on Pay Beta



Note: Panel (a) and panel (b) plot GDP beta estimates β_g that controls 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.

Future research could build on this work by rationalising these GDP betas and steady state labour market transition rates in a heterogeneous agent economic models of the business cycles, particularly models calibrated to the UK.

References

Amberg, N., Jansson, T., Klein, M. & Picco, A. R. (2022), 'Five facts about the distributional income effects of monetary policy shocks', *American Economic Review: Insights* **4**(3), 289–304.

Andersen, A. L., Johannesen, N., Jørgensen, M. & Peydró, J.-L. (2022), 'Monetary policy and inequality', *Univ. of Copenhagen Dept. of Economics Discussion Paper, CEBI Working Paper* **9**, 22.

Bauer, M. D. & Swanson, E. T. (2023), 'A reassessment of monetary policy surprises and high-frequency identification', *NBER Macroeconomics Annual* **37**(1), 87–155.

Bell, B., Bloom, N. & Blundell, J. (2022), 'Income dynamics in the united kingdom and the impact of the covid-19 recession', *Quantitative Economics* **13**(4), 1849–1878.

Blundell, R. & Preston, I. (1998), 'Consumption inequality and income uncertainty', *The Quarterly Journal of Economics* **113**(2), 603–640.

Broer, T., Kramer, J. V. & Mitman, K. (2022), 'The curious incidence of monetary policy across the income distribution'.

Cantore, C., Ferroni, F., Mumtaz, H. & Theophilopoulou, A. (2022), 'A tail of labor supply and a tale of monetary policy'.

Cesa-Bianchi, A., Thwaites, G. & Vicondoa, A. (2020), 'Monetary policy transmission in the united kingdom: A high frequency identification approach', *European Economic Review* **123**, 103375.

Grigsby, J., Hurst, E. & Yildirmaz, A. (2021), 'Aggregate nominal wage adjustments: New evidence from administrative payroll data', *American Economic Review* **111**(2), 428–471.

Guvenen, F., Schulhofer-Wohl, S., Song, J. & Yogo, M. (2017), 'Worker betas: Five facts about systematic earnings risk', *American Economic Review* **107**(5), 398–403.

Hoffmann, E. B. & Malacrino, D. (2019), 'Employment time and the cyclicality of earnings growth', *Journal of Public Economics* **169**, 160–171.

Holm, M. B., Paul, P. & Tischbirek, A. (2021), 'The transmission of monetary policy under the microscope', *Journal of Political Economy* **129**(10), 2861–2904.

Jentsch, C. & Lunsford, K. G. (2022), 'Asymptotically valid bootstrap inference for proxy svars', *Journal of Business & Economic Statistics* **40**(4), 1876–1891.

McKay, A. & Reis, R. (2016), 'The role of automatic stabilizers in the us business cycle', *Econometrica* **84**(1), 141–194.

Melolinna, M. & Tóth, M. (2016), 'Output gaps, inflation and financial cycles in the united kingdom', *Bank of England, Staff Working Paper 585* .

ONS (2015), 'A guide to sources of data on earnings and income'.

Stock, J. H. & Watson, M. W. (2018), 'Identification and estimation of dynamic causal effects in macroeconomics using external instruments', *The Economic Journal* **128**(610), 917–948.

Verbeek, M. (1996), Pseudo panel data, *in* 'The Econometrics of Panel Data: A Handbook of the Theory with Applications', Springer, pp. 280–292.

Appendix

A1: Data

Space to move/add some data construction material to the appendix

A2: 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.

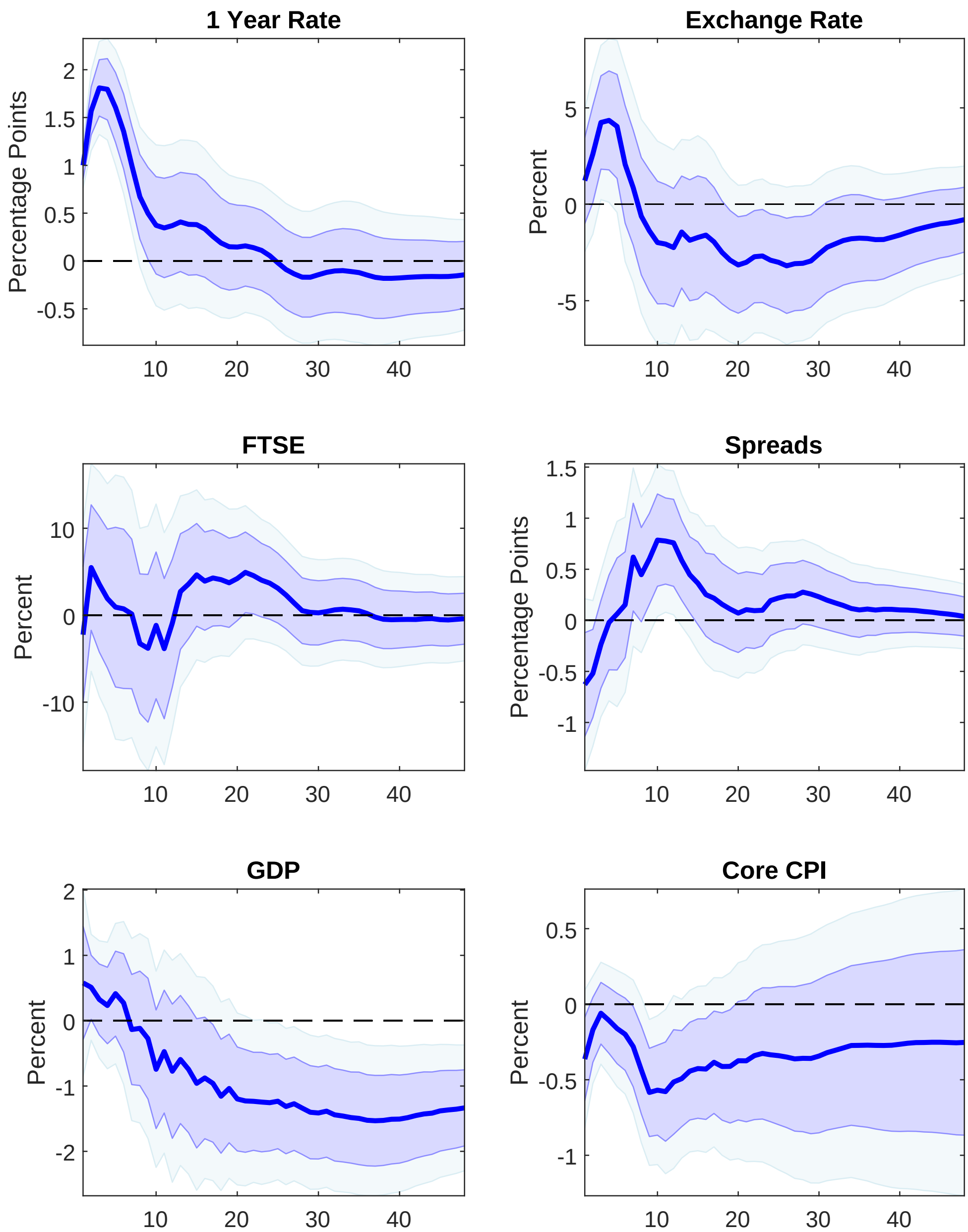
The VAR is estimated using monthly observations from 1996 to 2019 and 12 lags. The effect of monetary policy is identified using the external (proxy) instruments approach (see Stock & Watson (2018)). The instrument for monetary policy shocks is taken as the change in the price of sterling futures contracts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

$$\hat{z}_t = \beta x_{t-} + z_t \tag{7}$$

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.

A3: Further Results

Figure A2.1: 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 (see Jentsch & Lunsford (2022)) with centered confidence interval reported in blue for the 68 and 90 percent windows.