The Curious Incidence of Monetary Policy Across the Income Distribution*

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Abstract

We use high-frequency German administrative data to study the effects of monetary policy on income and employment across the earnings distribution. Earnings growth at the bottom of the distribution is substantially more elastic to policy shocks. This unequal incidence is driven by differences in the response of employment risk across the distribution: job loss is more countercyclical for lower-earnings households. Viewed through the lens of a standard incomplete-markets model, the heterogeneous incidence substantially amplifies the equilibrium response of aggregate consumption to shocks.

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1 Introduction

How do monetary policy interventions affect individuals' earnings and employment prospects across the income distribution? Does the unequal incidence of monetary policy across the distribution amplify or dampen the response of aggregate consumption to changes in interest rates or future consumption? The burgeoning heterogeneous-agent New Keynesian (HANK) literature has identified labor income as an important channel through which household heterogeneity impacts the transmission of monetary policy (inter alia, Auclert, 2019; Bilbiie, 2018; Hagedorn et al., 2019; Kaplan et al., 2018). Answers to the foregoing questions are key for understanding the transmission of monetary policy to the aggregate economy. However, there is little direct empirical evidence from large advanced economies on these transmission channels.

In this paper, we first empirically study the heterogeneous effects of monetary policy surprises on labor earnings across the income distribution. Our findings show that monetary policy has significantly larger effects on the earnings of low-income workers. This is mainly because their job-loss risk responds more strongly to interest rate changes than workers with higher incomes. This unequal incidence significantly reduces income inequality in response to monetary expansions. It has long-lasting effects on employment rates of poor workers, which remain elevated even years after the initial shock. Second, we use a structural model to show how this heterogeneous incidence of monetary policy on unemployment risk along the income distribution strongly amplifies its effect on aggregate demand. This holds relative to both a standard representative-agent model without unemployment risk and a model where unemployment risk is homogeneous across the distribution.

For our empirical analysis, we use a long panel of detailed German administrative data, containing individual labor market biographies including earnings. Labor market status is observed at a daily frequency. The high-frequency nature of our data allows us to estimate responses of earnings and labor market transition probabilities to monetary policy shocks and high-frequency changes in aggregate earnings. This sets our paper apart from the literature that empirically investigates the heterogeneous effects of business cycles on individual income risk using administrative data. Our dataset allows us to understand the importance of changes in employment status for earnings changes. The previous literature has speculated that the larger sensitivity of earnings at the bottom of the distribution was due to non-employment risk, our paper is, to our knowledge, is the first to show that this is the case.

We identify monetary policy surprises using high-frequency changes in Overnight Indexed Swap (OIS) rates for the Eurozone.[1] We then use the identified shock series for estimating the

[1]See e.g. Jarociński and Karadi (2020); Nakamura and Steinsson (2018), and Almgren et al. (2022) for

impact of shocks on labor earnings using local projections à la Jordà (2005). Monetary policy affects labor earnings most at the bottom of the permanent-income distribution. In response to an expansionary monetary policy surprise, earnings growth rises about three times as much in the bottom quintile as it does at the top. The differential growth is accounted for by a substantially stronger fall in separation rates into non-employment at the bottom of the distribution. In contrast, job-finding rates, while pro-cyclical, rise homogeneously across the distribution. Similarly, the earnings growth of workers who remain employed increases, but with mostly uniform effects across the income distribution.

These heterogeneous earnings responses across the distribution give rise to strong redistributional forces. An unexpected interest rate cut leads the Gini coefficient of labor earnings to fall significantly. In addition, monetary policy has significant effects on medium-run employment prospects: individuals who become unemployed in the month of a monetary policy expansion find jobs significantly faster, have significantly higher earnings and remain employed significantly longer.

To understand the implications of our empirical findings for the aggregate economy, we extend the framework of Werning (2015) to account for heterogeneous unemployment risk—the key force behind the heterogeneous earnings responses we document. Countercyclical unemployment risk amplifies the effect of interest-rate shocks on aggregate demand through precautionary savings, as workers who fear unemployment reduce their consumption in recessions by more than the fall in their permanent income. Heterogeneous incidence further amplifies the unemployment-risk channel because monetary policy affects the riskier workers who account for the bulk of precautionary savings. This positive association of level and cyclicality of risk in the cross-section makes aggregate precautionary savings more responsive to monetary policy. Our analysis suggests that this increase is quantitatively important, raising the consumption response to monetary policy interventions by about a third.

Relation to the literature

Our paper contributes to three broad strands of the literature. First, it contributes to the empirical literature that studies the cyclical nature of income risk, beginning with Storesletten et al. (2004). Our paper fits into the more recent focus of this literature that uses high-quality administrative data (Guvenen et al. (2014, 2017); Patterson et al. (2019) for the US, and for other countries Halvorsen et al. (2020) (Norway), Hoffmann and Malacrino (2019) (Italy), De Nardi et al. (2019), (Netherlands and US)). We contribute to this literature by providing evidence from another large advanced economy (Germany), and by showing that the cyclical

discussion of high-frequency identification of monetary policy shocks in the U.S. and Eurozone, respectively.

incidence of risk is the same for business cycle shocks as well as aggregate earnings movements induced by identified monetary policy shocks.

Second, our paper adds to the fast-growing literature studying how monetary policy affects households and individuals. An early important contribution (Coibion et al., 2012), which studies the impact of monetary policy shocks using data from the Consumer Expenditure Survey in the US. Three contemporaneous papers—Holm et al. (2020), Andersen et al. (2022), and Amberg et al. (2022) investigate this question for the cases of Norway, Denmark, and Sweden, respectively. They all find similar patterns: earnings are more strongly affected at the low end of the income distribution than they are around the median. At the top of the distribution, results are mixed. Our research documents the same pattern in Germany. The novelty of our contribution is decomposing the mechanisms underlying the result. We show that conditional on employment there is a small homogeneous response of earnings. We then show that the U-shaped pattern is driven by labor market transitions, and in particular the separation margin. Two other papers written subsequent to ours also investigate labor-market implications to monetary policy. Coglianese et al. (2022) studies a single monetary policy event in Sweden after the Global Financial Crisis and looks at the implications for unemployment. Cantore et al. (2022) study labor supply effects of monetary policy in the U.K. and U.S. economies. Finally, a closely related paper, Moser et al. (2021) also uses administrative data to study how negative interest rates following the European Debt Crisis in 2014 impacted credit supply to firms and the employment and wage prospects of their workers. We see this paper as highly complementary to ours, in that exploits a particular event study to dig further into the mechanisms driving the labor-market transitions that we document.

Third, our paper contributes to the literature that studies how unemployment risk can amplify aggregate fluctuations. The pioneering work of Krusell and Smith (1998) studied idiosyncratic and aggregate unemployment risk in a real model with self-insurance. Our paper is in the spirit of more recent contributions who have focused on the importance of nominal rigidities, including Acharya and Dogra (2020); Challe (2020); Den Haan et al. (2018); Gornemann et al. (2016); Graves (2020); Ravn and Sterk (2017, 2021). We contribute to that literature by providing a sufficient statistic and quantifying the extent to which heterogeneous unemployment risk amplifies aggregate demand fluctuations without having to rely on a fully specified model.

The rest of the paper is organized as follows. The next section presents the data and describes the structure of income and employment transitions in our sample on average. Section 2 describes how we identify monetary policy surprises, and how we use them to study their heterogeneous incidence across the earnings distribution. Section 5 investigates the implications of our findings for aggregate consumption responses to monetary policy shocks. Section 6 concludes.

2 Data

We use administrative social security data on a two-percent sample of all labor-market histories in Germany from the Sample of Integrated Employment Biographies (provided by the Research Data Center, FDZ).[2] This dataset contains about 1.7 million individuals but excludes civil servants and self-employed individuals. For our analysis, we utilize data on the years between 1995 and 2013. Each observation in the original dataset is a labor-market spell (Ganzer et al., 2017).[3] For our purposes, we convert these spells into monthly employment histories for each individual. Each such observation includes an individual's employment status and their average daily labor earnings, which we aggregate to the monthly level. Earnings are deflated using the Harmonized Index for Consumer Prices for Germany.[4] For about ten percent of individuals in our sample, earnings are top coded; we exclude these observations. All non-employed workers are coded to have zero income.

Because we are interested in the effect of monetary policy on labor earnings and employment status, we focus on individuals with a high degree of attachment to the labor market. In particular, we restrict our sample to employed individuals liable to social security without special characteristics, (thus excluding, for example, trainees and marginal part-time workers) and the unemployed, defined as individuals who received unemployment benefits (ALG I) at the beginning of their current non-employment episode.

We study the differences in the earnings responses to monetary policy across the income distribution. We classify individuals according to their permanent income, which we see as a key summary measure of welfare differences, but also because previous work has found strong heterogeneity along this dimension (Guvenen et al., 2017). Our preferred proxy for permanent income is average earnings over the five years preceding the month for which we calculate the earnings change, as in Guvenen et al. (2017).[5] Using this measure, in every such month, we sort individuals into quantiles, conditional on gender and five-year age brackets. We restrict

[2] We rely on the factually anonymous version of the Sample of Integrated Labour Market Biographies (SIAB-Regionalfile) – Version 7514. Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). Data access was provided via a Scientific Use File supplied by the FDZ of the BA at the IAB.

[3] Employment relationships longer than 12 months are split into multiple spells. We drop spells that are shorter than 1 month. Potentially missing spells are imputed according to Drews et al. (2007).

[4] Obtained from Eurostat, series prc_hicp_midx.

[5] Our estimation sample comprises the period between 2000M1 to 2012M12. However, we make use of data from 1995 in order to compute our backward-looking permanent income measure, but only consider monetary policy surprises from 2000M1 to 2013M12.

the sample to workers who have at least one earnings observation in the above+mentioned five year period, in order to avoid bunching at zero. Furthermore, we exclude individuals whose earnings exceed the maximum amount liable for social security contributions, because their incomes are top-coded at that limit. For these workers, we cannot compute reliable earnings growth rates. After applying these sampling restrictions, we are left with close to 800,000 individuals across our sample period and around 300,000 individuals in each month.

To understand how key observables evolve along our permanent income distribution (henceforth simply the "income distribution"), Table 1 reports descriptive statistics across deciles for the month of January 2010.[6]

Table 1: Averages within deciles of permanent income, first quarter 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
HS or Technical College	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.07	0.10
Vocational training	0.77	0.81	0.82	0.83	0.84	0.83	0.83	0.81	0.78	0.69
University	0.05	0.04	0.04	0.05	0.04	0.05	0.06	0.08	0.11	0.19
Monthly earnings	1083.56	1485.31	1780.65	2021.29	2247.89	2492.38	2754.80	3076.01	3483.33	4328.60
Employed	0.76	0.89	0.94	0.96	0.97	0.98	0.98	0.99	0.99	0.98
Job finding	0.38	0.53	0.56	0.55	0.54	0.54	0.56	0.55	0.54	0.52
Job loss	0.07	0.06	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.03
Observations	28878	28871	28872	28870	28869	28875	28871	28871	28872	28866

Note: The table shows values of different variables averaged within deciles of the permanent income distribution in January 2010. Deciles are computed conditionally on five-year age brackets and gender. We impute education following the imputation procedure in Fitzenberger et al. (2005). Monthly earnings are in current Euros, all others are fractions. Job-finding and job-loss refer to U to E and E to U transitions over twelve months, respectively. The deciles are computed conditional on age and gender. These variables are thus not reported.

In our dataset, education is measured by a categorical variable. More than 70 percent of all individuals in our sample indicate vocational training as their highest qualification, and education levels are very similar across the first 8 deciles. In the last two deciles, the share of university educated individuals rises but never exceeds 20%. The gradient of nominal earnings across the distribution is substantial, with average earnings in the top decile about four times higher than in the first. In 2010, the social security contribution limit was about 5400 euros per month, beyond which we drop individuals. This explains the seemingly low value of average earnings in the top decile. Employment rates are high in this sample of highly-attached individuals. They average 76 percent in the bottom decile, and rise steeply across the bottom half of the distribution to flatten out around 98 percent above the median. Job-finding rates (defined as 12-month transitions of the unemployed into employment) are

[6]Note that, with some abuse of language but hopefully no room for confusion, we call deciles both the 9 points of the distribution as well as the 10 groups they define (we proceed similarly for other quantiles). The quantiles are computed conditional on age and gender. These variables are thus not reported in Table 1.

between 50 and 60 percent in all deciles but the first, where they are substantially lower (about a third). Job-loss probabilities (similarly defined) fall monotonically, from seven to two percent, across the distribution.

3 Estimation strategy

3.1 Identifying monetary policy surprises

We focus on the period between January 2000 and December 2013, when European monetary policy was conducted by the ECB.[7] Since the German economy accounts for roughly one-quarter of Euro-area GDP it is likely that the ECB's monetary policy was heavily influenced by German economic performance. Hence, when estimating the impact of interest rate changes on the German economy, endogeneity is an important concern.

To identify monetary policy surprises our approach follows Almgren et al. (2022), who rely on high-frequency changes in Overnight Indexed Swap (OIS) rates. We use these changes to instrument for unexpected changes in the ECB's policy rate, which we denote as Δi_t. Every six weeks, on Thursdays, the ECB governing council meets to decide on monetary policy actions. At 13:45 CET, a press release is posted, which concisely summarizes the decisions taken by the governing council. Subsequently, at 14:30 CET, the president of the ECB holds a press conference, first motivating the decisions taken in an introductory statement and later taking questions from the audience. Our instrument, Z_t, equals the change in 3-month EONIA OIS rates in response to each of these two events in a narrow time window around them. If this measure is large, in absolute terms, we conclude that the decisions taken by the ECB Governing Council were not expected by financial markets and vice versa. The identifying assumption underlying the approach is that no other news are released during the above-mentioned short time windows which have an impact on the effectiveness of monetary policy.[8]

Our main empirical specification to estimate the effects of monetary policy surprises on economic variables is the following regression:

$$x_{t+h} - x_{t-1} = \alpha_h + \beta_h \Delta i_t + \gamma_h X_{t-1} + \varepsilon_{t,h} \tag{1}$$

where x_{t-1} represents the value of the economic variable in question one period before the monetary policy surprise, and x_{t+h} represents its value h periods after the shock. We condition

[7] The high-frequency identification approach outlined here cannot be implemented for earlier time periods, as the Bundesbank did not relay its policy decision on a precisely planned schedule on the announcement day.

[8] For more information, see Almgren et al. (2022).

this growth rate on x_{t-1}, as opposed to x_t, because it is conceivable that monetary policy has contemporaneous effects on x_t, which would invalidate all growth rates going forward. The vector X_{t-1} represents a set of control variables consisting of three lags of (i) the instrument Z_t, (ii) aggregate earnings and (iii) Δi_t, as well as calendar month dummies to control for seasonality. As the policy rate, we use the Euro Overnight Index Average (EONIA).

3.2 Aggregate effects of monetary policy

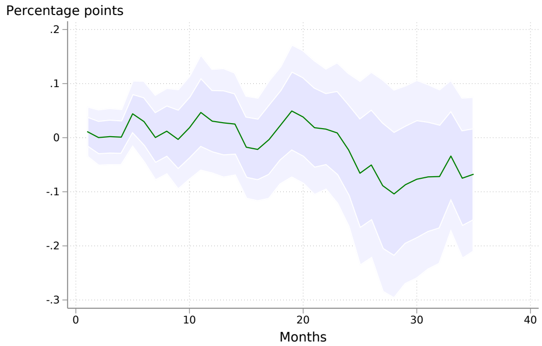
Before moving to individual incomes, we investigate the effect of monetary policy shocks on the aggregate economy in Germany. To this end, we estimate the regression in Equation (1), replacing x with (i) the logarithm of the HICP price index for Germany, (ii) the logarithm of interpolated real GDP, (iii) the official German unemployment rate, and (iv) the real interest rate, computed as the change in the logarithm of the German price index between months $t+1$ and t subtracted from the ECB's policy rate in period t; we also augment the vector of control variables X_t with three lags of the left-hand side variable.[9]

Figure 1 shows the impulse responses to an expansionary monetary policy surprise one standard deviation (following Gertler and Karadi, 2015), estimated using Equation (1). The horizontal axis measures the time after the monetary policy shock in months, the vertical axis measures the percentage point change in the variable in question. The top left panel indicates that the inflation rate does not significantly react to the surprise in either direction. The response of industrial production is reported in the top right panel. According to the textbook theory of monetary policy, production should contract following a monetary tightening. The graph indicates that this is the case. The unemployment rate (bottom left panel) increases slowly but significantly so. The real interest rate increases after the monetary policy shock, but then returns to zero after about 1.5 years. Most of the subsequent estimates are insignificant.

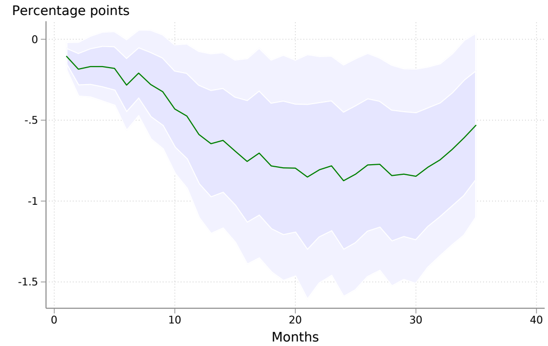
In addition to standard macro aggregates, Figure 12 in the appendix plots the change in aggregate earnings (i.e., average earnings across all individuals) and the employment share for our full sample. The left panel shows that the response of earnings to a contractionary monetary policy surprise of one-standard-deviation builds up gradually, reaching a point estimate of about 0.5 percentage points after two years. This reduction in average earnings is accompanied by a fall in the share of workers who are employed.

[9] We use the GDP series from Almgren et al. (2022), who interpolate it, with the method proposed by Chow and Lin (1971), using industrial production, unemployment and retail trade.

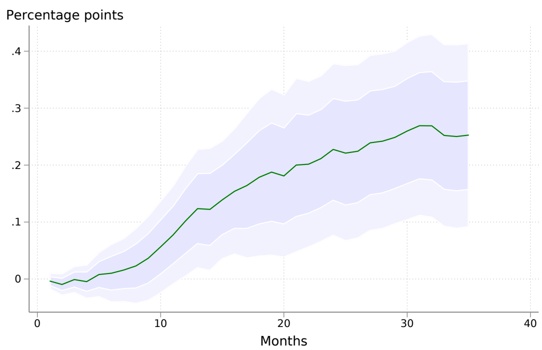
Figure 1: Aggregate responses to monetary policy surprises



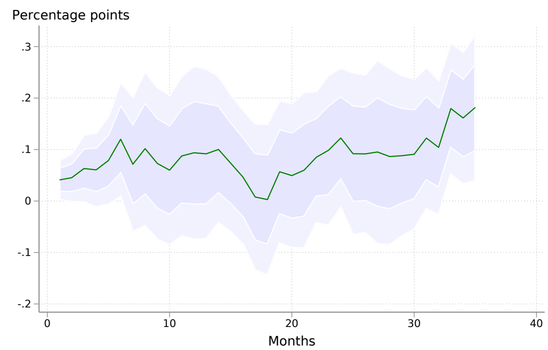
(a) Inflation rate



(b) Interpolated GDP



(c) Unemployment rate



(d) Real interest rate

Note: The figure shows the impulse responses of aggregate variables to a surprise expansion of one standard deviation, estimated using the LPIV outlined in Equation (1). The *Top Left Panel* shows the change in the inflation rate, calculated as the change in the logarithm of the HICP for Germany. The *Top Right Panel* shows the percentage change in interpolated real GDP (as in Almgren et al., 2022), calculated as the log difference between t and $t+h$, and the *Bottom Left Panel* shows the change in the unemployment rate. The *Bottom Right Panel* shows the change in the real interest rate, calculated as the inflation rate subtracted from the policy rate. The sample period is from 2000 until 2013. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC standard errors.

4 The impact of monetary policy across the distribution

4.1 Earnings growth

Our main goal is to estimate the effect of monetary policy surprises on earnings growth rates, separately for individuals in different quantiles of the permanent income distribution. As described in Section 2, we sort individuals into quantiles based on their permanent income in period $t-1$. We split the distribution into 20 quantiles, or ventiles, conditioning on age and gender. For each of these quantile groups, we first compute average earnings as

$$\overline{earn}^q_{t+h} = \frac{1}{N^q}\sum_{i=1}^{N_q} earn_{i,t+h} \quad \forall i \in q \text{ at } t-1$$

where $earn_{i,t+h}$ represents the labor earnings of an individual in month $t+h$ who was sorted into quantile q in month $t-1$.

Next, in Equation (1), we set $x_{t+h} = \log(\overline{earn}_{t+h})$ and, for each quantile, estimate

$$\Delta \log(\overline{earn}^q_{t+h}) = \alpha_h + \beta^q_h \Delta i_t + \theta X_t + \epsilon^q_{t+h} \tag{2}$$

where $\Delta x_{t+1} = x_{t+h} - x_{t-1}$. The coefficient β^q_h captures the effect of a 100 basis point change in interest rates Δi_t, in period t, (instrumented by Z_t, as described in Section 3, following Stock and Watson (2018)) on earnings growth in quantile q between periods $t-1$ and $t+h$.

We scale the size of the exogenous interest rate change, Δi, such that it causes a 1 percentage point increase in the growth rate of *aggregate* earnings, twelve months after the shock.[10] This allows us to compare the change in earnings growth rates across quantiles associated with an *unconditional* one-percent change in aggregate earnings (as in Guvenen et al. (2017)) to that of a *conditional* change in aggregate earnings of equal size, caused by a monetary policy innovation:

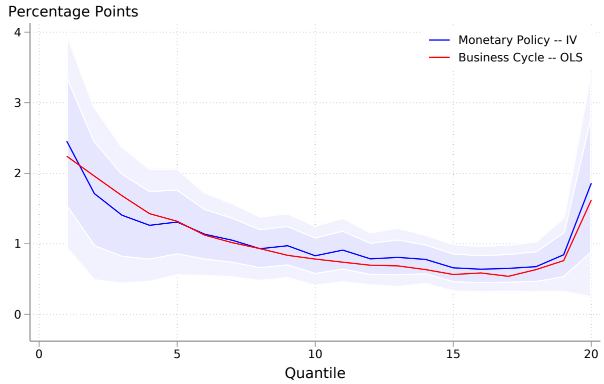
$$\Delta \log(\overline{earn}^q_{t+h}) = \alpha_{Y,h} + \beta^q_{Y,h} \Delta \log(\overline{earn}_{t+h}) + \theta X_t + \epsilon^q_{Y,t+h}. \tag{3}$$

Here, the coefficient $\beta^q_{Y,h}$ represents the change in the quantile-specific earnings average in response to an unconditional change in the overall earnings average.

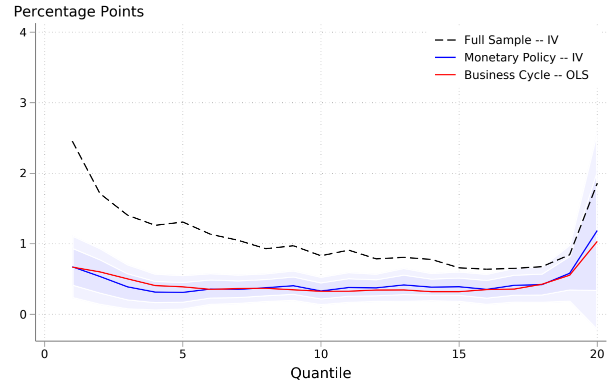
The blue line in the left panel of Figure 2 reports the quantile-specific earnings changes between months $t-1$ and $t+12$, induced by an exogenous interest rate change which raises aggregate earnings by one percentage point over the same period. Recall that, since the maximum length of an employment spell in our dataset is twelve months, earnings growth between $t-1$ and $t+12$ is always computed using earnings observation drawn from two different employment spells.

[10]For reference, the left panel of Figure 12 plots the response of aggregate earnings in our sample to an exogenous *one-standard-deviation* rise in the policy rate. Aggregate earnings fall by roughly 0.4 percentage points. Hence, to induce a 1 percentage point rise in aggregate earnings, the policy rate must fall by moer than twice as much.

Figure 2: Regression coefficients β_{12}^q across the income distribution



(a) Full sample



(b) Only individuals employed in $t-1$ and $t+12$

Note: The *Left Panel* plots the coefficients β_{12}^q in Equation (2) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings) and $\beta_{Y,12}^q$ in Equation (3), separately for individuals who shared the same ventile of the permanent income distribution in period $t-1$. The *Right Panel* compares the coefficients β_{12}^q for the full sample across ventiles (gray dashed line) to $\beta_{12}^{q,E}$ and $\beta_{Y,12}^{q,E}$, estimated on a smaller sample of individuals who are employed both in period $t-1$ and $t+12$ (the blue and red lines, respectively). Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.

Earnings changes in response to expansionary monetary policy exhibit a pronounced U-shape across the permanent income distribution. In particular, the earnings of the poorest individuals, in the bottom ventile, respond almost three times as much as earnings at the median. Moving up the income distribution, this response declines strongly in magnitude, to about two-thirds of the median effect in ventiles 15 to 19.[11] Earnings of the income-rich, in the top ventile, respond more, about twice as strong as median earnings.[12] Both Andersen et al. (2022) and Amberg et al. (2022) find similar patterns for Denmark and Sweden, respectively; Cantore et al. (2022) documents a similar pattern in the US using data from the CPS.[13]

The red line in the left panel of Figure 2 depicts the point estimates $\beta_{Y,12}^q$, summarising the comovement of individual and aggregate earnings growth rates without conditioning on monetary policy surprises. As documented in Guvenen et al. (2017) for the US economy, this comovement also has a U-shaped relationship with the level of individual permanent incomes,

[11]In Appendix B.7, we dicuss which coefficients are significantly different from each other.

[12]Our results are robust to the inclusion of unemployment benefits (see Appendix B.1), to alternative definitions of permanent income (see Appendix B.2) and to different measures of monetary policy surprises (see Appendix B.3)

[13]In Andersen et al. (2022), the U-shape in earnings responses is less pronounced. We conjecture that this is due to the fact that in their approach, individuals are sorted into an income distribution based on incomes including transfers. Hence, their distribution includes individuals that are only partially attached to the labor force, especially towards the bottom. Our approach excludes those individuals.

very similar to that of earnings changes due to monetary policy (although with a somewhat less pronounced increase in the extreme ventiles).

The estimates of β_{12}^q, depicted in the left panel of Figure 2, conflate the effect monetary policy has on labor earnings with the effect it has on employment probabilities, as they are based on the changes in average labor earnings of all individuals in a given quantile (including the unemployed who have zero labor earnings). However, because average earnings across quantiles, $\overline{earn}_t^q$, equal the product of the average labor earnings of the employed, $\overline{earn}_t^{q,E}$ times the employment rate, we can compute the following decomposition

$$\log(\overline{earn}_{t+h}^q) = \log\left(\overline{earn}_{t+h}^{q,E}\right) + \log\left(\frac{N_{t+h}^{q,E}}{N_{t+h}^q}\right) \tag{4}$$

where $\overline{earn}_{t+h}^{q,E}$ represents the average earnings of employed individuals in month $t+h$, who were sorted into quantile q in period $t-1$. In the second expression, $N_{t+h}^{q,E}$ represents the number of employed individuals in period $t+h$ who were sorted into quantile q in period $t-1$. Thus, Equation (4) implies that changes in average labor earnings across quantiles are the sum of two separate effects: the changes in the labor earnings of the employed (which we denote the *intensive*-margin effect), and changes in the employment rate (*extensive*-margin effect).

To isolate the heterogeneity in the intensive-margin effect, we substitute the change in average earnings of the employed, $\overline{earn}_{t+h}^{q,E}$, in place of its full-sample counterpart $\overline{earn}_{t+h}^q$ in Equation (2). The resulting coefficients, which we refer to as $\beta_{12}^{q,E}$, are displayed in the blue line in the right panel of Figure 2. As before, we scale the point estimates such that the initial exogenous interest rate change Δi causes aggregate earnings growth to rise by one percentage point over the subsequent twelve months.[14]

Earnings of the employed appear to be much less affected by monetary policy surprises than earnings in the full sample. The estimates are less heterogeneous across the distribution and substantially smaller in magnitude. In response to an exogenous change to the policy rate, the earnings growth of the employed rises by about 0.7 percentage points in the first quantile. Across the first five quantiles, the point estimate of this effect declines somewhat, but is essentially flat between ventiles 9 and 19, before rising substantially (but not significantly) in the top ventile. The difference between the estimates of β_{12}^q (dashed black line) and $\beta_{12}^{q,E}$ is most pronounced in the bottom ventile, where the extensive margin of employment accounts for two thirds of monetary policy's effect on average labor earnings. This role of the extensive margin declines across the income distribution, to about a quarter of the overall effect.

[14] The top panel of Figure 14 in the Appendix shows the procyclicality of the second component across the income distribution.

In the next subsection, we investigate how monetary policy affects labor market transition probabilities.

4.2 Labor market transitions

We observe each individual in our sample either as employed or as unemployed. Let $s_{i,1}$ be an individual's labor market status in period $t-1$ and $s_{i,2}$ be the labor market status of the same individual in some future period $t+h$. Then, there are four different transitions between $s_{i,1} \in \{E, U\}$ and $s_{i,2} \in \{E, U\}$. In addition, we also identify a subset of "switchers" who are observed as employed in both periods, but with different employers ($s_2 = switch$).

For each quantile along the permanent-income distribution, we aggregate the individual transitions into transition probabilities:

$$TR_{t+h}^{q,s_1,s_2} = \frac{1}{N^{q,s_1}} \sum_{i \in q, s_1} \mathbb{I}_{s_1,s_2}.$$

According to this definition, TR_{t+h}^{q,s_1,s_2} is the fraction of all individuals who are sorted into quantile q in period $t-1$ and observed in state s_1 at $t-1$ (N^{1,s_1}), who have transitioned to state s_2 by period $t+h$.

Similarly to Equation (2), we then estimate the following regression separately for each quantile-subsample:

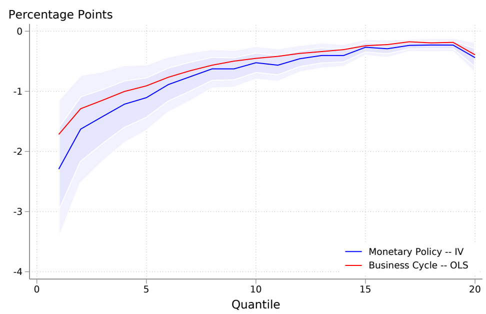
$$TR_{t+h}^{q,s_1,s_2} = \alpha + \gamma_h^{q,s_1,s_2} \Delta i_t + \theta X_t + \epsilon_{t+h}^{q,s_1,s_2} \tag{5}$$

where the coefficient γ_h^{q,s_1,s_2} measures the percentage point change in the share of individuals in state s_1 that make a particular labor market transition in response to a monetary policy surprise, for a given quantile q. Again, the vector X_t contains calendar-month dummies and three lagged values of Δi_t, aggregate earnings, and Z_t.

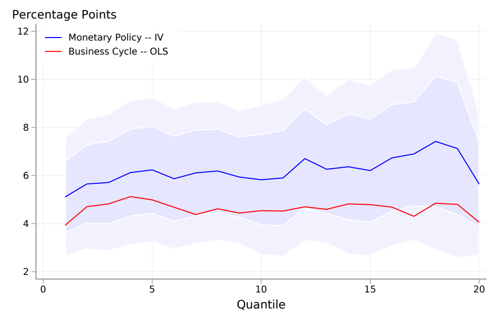
The blue line in the top left panel of Figure 3 shows the point estimates for $\gamma_{12}^{q,E,U}$ (again scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings), summarising the effect of a monetary policy surprise on transitions from employment to unemployment. As with earnings, we document strong heterogeneity in the incidence of monetary policy surprises along the income distribution. For the poorest individuals in the sample, the interest rate change significantly decreases the probability of moving to unemployment by on average two percentage points. Moving up the income distribution this effect declines monotonically to less than 0.5 percentage points. The top ventile is again affected somewhat more strongly.

Analogous to section 4.1, we can compare the estimates conditional on monetary policy with those of unconditional comovement between transition probabilities and aggregate earnings changes.[15] The resulting coefficients are displayed as the red line in the top left panel of Figure 3. Interestingly, the reduction in transitions into unemployment is somewhat more pronounced for the expansionary monetary policy shock than for an unconditional increase in aggregate earnings. The difference is largest at the low end of the permanent income distribution.

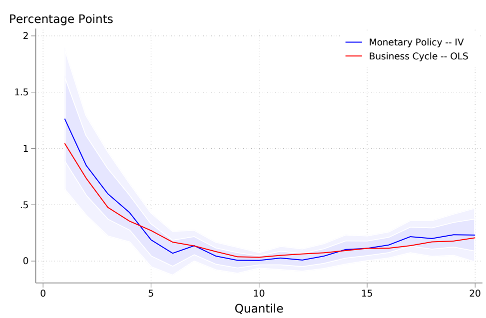
Figure 3: Regression coefficients γ_{12}^{q} across the income distribution



(a) E to U



(b) U to E



(c) Switch

Note: The *Top Left Panel* plots the coefficients $\gamma_{12}^{q,E,U}$ in Equation (5) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings, blue line) and $\gamma_{Y,12}^{q,E,E}$ (red line), from a version of Equation (5) which quantifies unconditional comovement (see text). Both quantify the change in transition probabilities for the employed in $t-1$ to employment in period $t+12$ (E to E). The *Top Right Panel* plots the scaled coefficients $\gamma_{12}^{q,U,E}$, and $\gamma_{Y,12}^{q,U,E}$, for the share of unemployed transiting to employment (U to E). The *Bottom Panel* plots the scaled coefficient $\gamma_{Y,12}^{q,switch}$ and $\gamma_{Y,12}^{q,switch}$ for the share of the employed who change employment relation. Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC standard errors. The sample period is 2000-2013.

The top right panel of Figure 3 shows the scaled point estimates for $\gamma_{12}^{q,U,E}$, summarising the effect of an expansionary monetary policy surprise on the probability of unemployed

[15]The regression is of the same form as Equation 5, with Δi substituted for with changes in aggregate income ΔY. We label the resulting coefficient $\gamma_{Y,h}^{q,s_1,s_2}$.

individuals transitioning to employment. This effect is on average more than 5 percentage points. Contrary to the stronger effect on the likelihood of E-to-U transitions, U-to-E transitions respond slightly less to monetary policy at the bottom of the distribution. In particular, while monetary policy shocks affect the transition probabilities of the income-poor similarly to average fluctuations (as summarised by their comovement with average earnings, in the red line), a gap between the two opens up along the income distribution.

The results in the top panels of Figure 3 thus show that the substantially stronger extensive-margin effect of monetary policy on employment shares of the poor is largely accounted for by their more responsive employment-to-employment transitions. The bottom panel of Figure 3 further investigates the source of this heterogeneity. It shows the scaled point estimates for $\beta^{switch}_{TR,12}$, summarising the effect of monetary policy surprises on the frequency of transitions between two different employment relationships. An expansionary monetary policy surprise makes job-switching more likely in the bottom quartile, but has little effect in the rest of the distribution. A similar pattern holds for the effect on job-switching of unconditional fluctuations in average earnings.

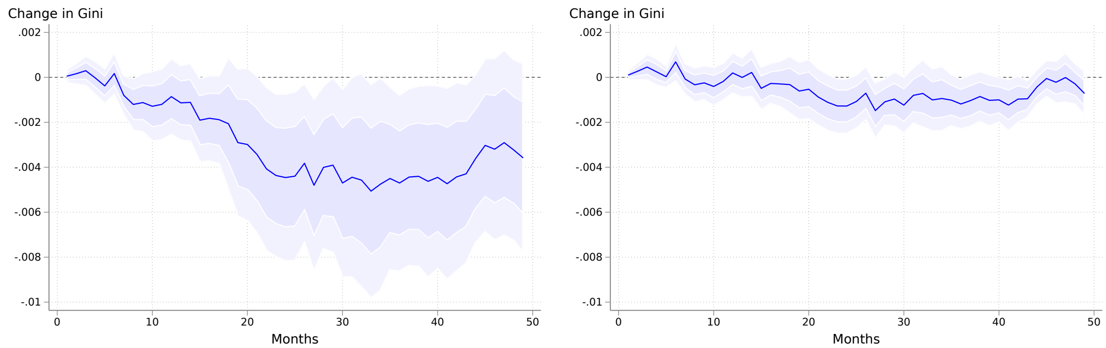
4.3 Inequality

The previous results beg the question how inequality in labor earnings develops in response to changes in monetary policy. To investigate this, we substitute values of the aggregate monthly Gini coefficient, $gini_{t+h}$, for x in Equation (1). Importantly, we include unemployed individuals in our calculations, with their labor earnings set to zero, as above.

The left panel in Figure 4 plots the change in the Gini coefficient in response to an expansionary monetary policy shock over time.[16] Inequality falls for two years after the shock, then reverts back. Throughout our sample period, the average value of the Gini coefficient is close to 0.3, implying that monetary policy has economically significant effects on this measure, decreasing it by close to three percent at the trough of the impulse response function in Figure 4.

[16] As before, the monetary policy surprise is scaled to cause aggregate earnings to rise by one percentage point over twelve months.

Figure 4: Gini coefficient Impulse Response



(a) Change in Gini (b) Change in Gini, including benefits

Note: The *Left Panel* shows the change in the Gini coefficient of labor earnings (including zeros), $gini$, in response to an expansionary monetary policy surprise, consistent with a one-percent increase in aggregate earnings, over time. The *Right Panel* shows the change in the Gini coefficient of labor earnings, including unemployment benefit receipts, $gini^{UI}$, in response to an expansionary monetary policy surprise, consistent with a one-percent increase in aggregate earnings, over time. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC standard errors. The sample period is 2000-2013.

Because our dataset also includes some information about unemployment benefit receipts, we can calculate the Gini coefficient taking these benefits into account. Analogous to before, we substitute $gini^{UI}_{t+h}$ into Equation (1) and compute the impulse response of this statistic to an expansionary monetary policy surprise. The implied change in inequality, plotted in the right panel of Figure 4, is substantially smaller, compared to the case when the unemployed's earnings are set to zero. Although $gini^{UI}$ decreases significantly, after about two years, the change is economically small: one percent relative to its average value. The unemployment benefit system, therefore, appears to attenuate the effect that monetary policy has on inequality.

4.4 Earnings and labor market prospects after unemployment

Figure 3 shows that much of the effect of monetary policy on average earnings, and most of its heterogeneous incidence, is due to the response of labor market transitions between employment and unemployment. However, the previous section only investigates a short, 12-month window of labor market transitions. Because the costs of unemployment are strongly affected by its duration and effect on future earnings, this section investigates the longer-run effects of monetary policy shocks on re-employment probabilities and earnings after unemployment. For this, we compare two groups of individuals: workers who become non-employed in the period of the surprise (t) and those who retain their jobs in t. We then investigate how earnings of the second group evolve relative to the first, and how monetary policy affects the difference. For $h = -6, -5, ..., 36$ we run the following regression for three terciles of our permanent income distribution:

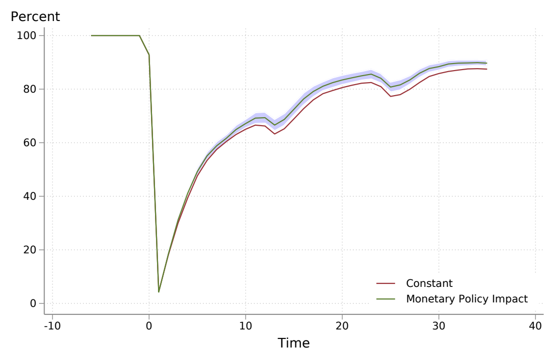
$$x_{t+h} = \alpha_{x,h} + \gamma_{x,h}\Delta i_t + \theta_{x,h} X_t + \epsilon_{x,t}. \tag{6}$$

where, $x \in \{earn, emp\}$ corresponds to the ratio of (i) average monthly earnings ($earn_{i,t}$) or (ii) the average employment rate $emp_{i,t}$ between individuals who become unemployed in period t and those who do not. Again, Δi_t represents the interest rate change in period t, instrumented using Z_t as before, and X_t contains calendar-month dummies and three lags of the interest rate change, the instrument and aggregate earnings. In Equation (6), $\alpha_{x,h}$ equals the average earnings or employment ratio h months after an unemployment shock in the absence of monetary policy surprises, between the two groups. In turn, $\gamma_{x,h}$ quantifies the impact of monetary policy on these variables. The regressions are similar in spirit to that in Davis and Von Wachter (2011), who also investigate earnings paths of the unemployed relative to those who remain employed. We focus on individuals who become unemployed after being employed for at least 6 months. Because this substantially reduces the sample size, we report results for terciles, rather than ventiles, of the permanent income distribution.

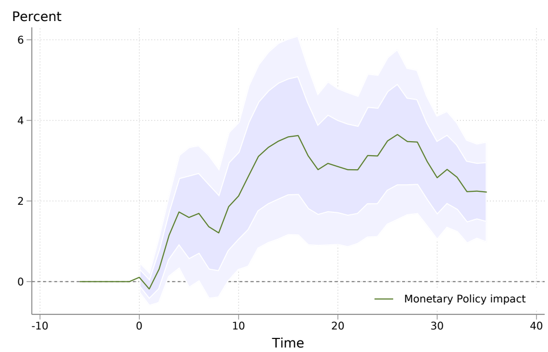
The top panels of Figure 5 show the results of the exercise for employment probabilities in the first tercile. Results for the second and third terciles are summarized in the bottom panel of the same figure. The red line in the top left panel shows the probability of being employed for individuals who transitioned to unemployment in period 0 relative to those who did not. This probability falls to almost zero after the unemployment event, but rises back to more than 60% 12 months after. Note that an individual is counted as employed if they were employed for at least half of the month. In the figure, the only slight drop in earnings at period 0 is explained by the fact that most individuals transition to unemployment on the last day of the month (i.e., they are observed as employed on the last day of the month, but not on the first of the subsequent month). The steep re-employment slope is likely due to the fact that our sample is comprised of individuals who are closely attached to the labor force. The green line in the same graph shows how an expansionary monetary policy surprise, which causes aggregate earnings to rise by one percent over twelve months, affects the employment probability. The probability rises by about three percentage points one year after the unemployment event. This is in line with the results reported in Figure 3, for more granular sorting. The right panel in Figure 5 isolates the effect of monetary policy. It rises for about 12 months and then stabilizes.

The results for the other terciles are similar, but the effect materializes later after the shock, as evident from the bottom panel in Figure 5. In the second tercile, monetary policy appears to have no significant effects on employment probabilities initially. The effect in the third tercile is more similar to the first, again implying a U-shaped pattern across terciles, similar to the one seen in the previous section. After two years, the effects of monetary policy are not significantly different across terciles.

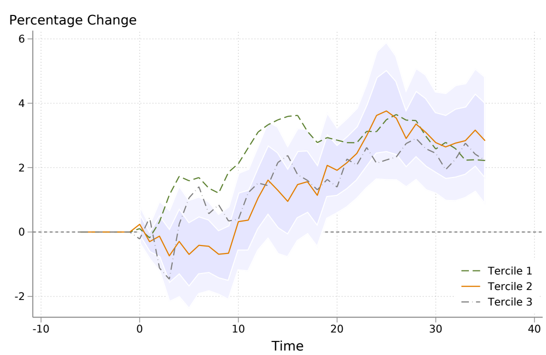
Figure 5: Effect of monetary policy shock on re-employment probabilities



(a) First tercile



(b) First tercile – Difference

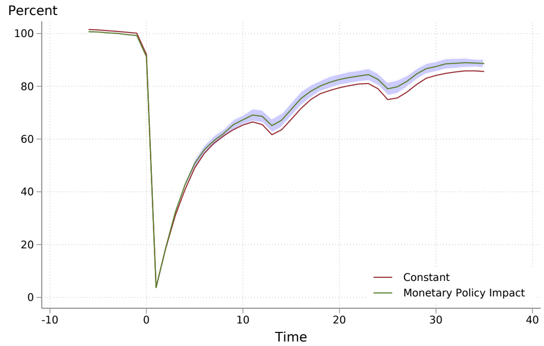


(c) Employment

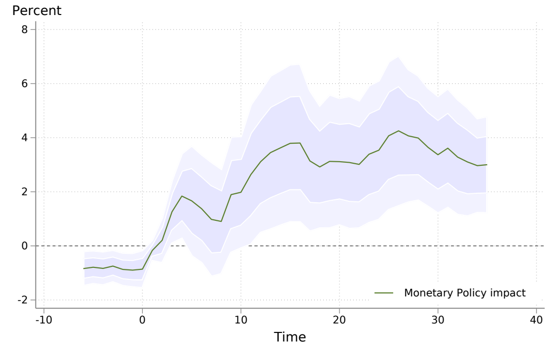
Note: The *Top Left Panel* shows the employment probability of individuals in the first tercile who transition into unemployment in month $t = 0$, relative to those who don't (red line). The green line shows how this probability changes after a monetary policy surprise (scaled to be consistent with a one-percent increase in aggregate earnings). The shaded area indicates the 90 percent confidence band based on HAC standard errors. The *Top Right Panel* isolates the effect of a monetary policy surprise on the employment probability, i.e. the difference between the two lines. The *Bottom Panel* shows the same effect for all three terciles. The dashed green lines represent estimates for the first tercile, the solid yellow lines those for the second and the dash-dotted grey line those for the third. The shaded areas in the top right and bottom graph represent 68 and 90 percent confidence bands based on HAC standard errors for the second tercile. Terciles are constructed based on average earnings during the five years prior to the start of the unemployment episode in period 0, conditional on gender and five-year age brackets. The sample period is 2000-2013.

Figure 6 shows the results for the same exercise using earnings as the dependent variable. Again, the results in the top left panel represent earnings of individuals who become unemployed in period 0 relative to those who do not. Naturally, earnings approach zero in the first month after the transition into unemployment. However, some individuals find new jobs in the same month, implying positive average earnings. An accommodative monetary policy surprise steepens the slope of this recovery. As shown in the top right panel, such a shock increases earnings by about three percent, 20 months after unemployment. These effects are stronger than for the other two terciles, plotted in the bottom panel of the same figure. For the second decile, especially, the positive effect of monetary policy on earnings only materializes after close to two years.

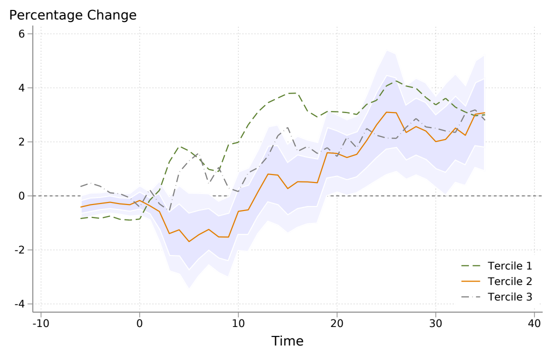
Figure 6: Effect of monetary policy on average earnings after unemployment



(a) First tercile



(b) First tercile – Difference



(c) Earnings

Note: The *Top Left Panel* shows the average earnings of individuals in the first tercile who transition into unemployment in month $t = 0$, relative to those who don't (red line). The green line shows how relative earnings change after a monetary policy surprise (scaled to be consistent with a one-percent increase in aggregate earnings). The shaded areas indicate 90 percent confidence intervals based on HAC standard errors. The *Top Right Panel* isolates the effect of a monetary policy surprise on the relative earnings, i.e. the difference between the two lines. The *Bottom Panel* shows the same effect for all three terciles. The dashed green lines represent estimates for the first tercile, the solid yellow lines those for the second and the dash-dotted grey line those for the third. The shaded areas in the top right and bottom graph represent 68 and 90 percent confidence bands based on HAC standard errors for the second tercile. Terciles are constructed based on average earnings during the five years prior to the start of the unemployment episode in period 0, conditional on gender and five-year age brackets. The sample period is 2000-2013.

Together, Figures 5 and 6 show that monetary policy indeed has long-run effects on individual earnings that persists substantially beyond the 12-months horizon that the previous sections focus on. Moreover, the effect on employment probabilities also accounts for a large fraction of these long-run earnings-effect of monetary policy. The most pronounced differences in the responses across the income distribution, however, are found at shorter horizons. These conclusions are robust to the inclusion of unemployment benefits into the earnings definition, as we show in Appendix B.1.

5 Implications for aggregate demand

Recent literature has pointed out that cyclical variations in employment risk may act as an amplifying mechanism for business cycles (Broer et al., 2021; Graves, 2020; Krueger et al., 2016). If workers reduce consumption and build up precautionary savings when separation risk rises (in recessions), the resulting contraction in demand could deepen the downturn. In this section, we explore how the heterogeneity we document in Section 4.1 affects the dynamics of aggregate demand in response to monetary policy shocks. We differ relative to previous analyses that abstract from heterogeneous incidence of unemployment risk (Acharya and Dogra, 2020; Auclert, 2019; Patterson et al., 2019). In our theoretical analysis, we follow Werning (2015) and focus on the household "demand block" without explicitly specifying the supply side of the economy. We consider an extension of his framework to account for job-finding and separation risk, and heterogeneity in risk across the distribution of earnings.

5.1 A model with heterogeneous employment risk

The economy is populated by a unit measure of households. There is a finite set of household types indexed by $i \in I$, with measures $\mu^i > 0$, such that $\sum_{i \in I} \mu^i = 1$. Households have identical preferences over consumption:

$$u = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(c_t(s^t)) \tag{7}$$

where c_t is consumption, $s_t \in S^i$ represents an idiosyncratic shock that follows a stochastic process that is identical and independent across households and s^t is the history of such shocks from 0 to t. We assume $U(c) = \frac{c^{1-\sigma}}{1-\sigma}$ (CRRA preferences). Household income $y_t^i(s_t)$ can depend on realizations of the idiosyncratic shock s_t and aggregate income Y_t according to:

$$y_t^i(s_t) = \gamma_t^i(s_t, Y_t). \tag{8}$$

Households can save and borrow in one-period risk-free bonds, b_t, subject to a type-specific borrowing constraint $-B_t^i(s_t, Y_t)$. The household budget constraint is thus given by:

$$c_t + b_t \leq y_t^i(s_t) + R_{t-1} b_{t-1} \tag{9}$$

where R_t is the real interest rate on risk-free bonds.

The cross-sectional distribution of households across idiosyncratic states and bond holdings is denoted $\Omega(s, b)$. The equilibrium definition is standard, such that households optimize, markets clear and the evolution of the cross-sectional distribution is generated from the optimal policy choices of households and the stochastic process for s_t.

5.1.1 Cyclical employment risk

Our empirical findings in Section 4.1 illustrate that:

1. Conditional on staying employed, the cyclicality of earnings growth is (approximately) uniform across the income distribution, and earnings growth is less cyclical than aggregate earnings growth

2. Employment risk is countercyclical, and substantially more so at the bottom of the distribution

We can capture these empirical findings in the model with the following specification, extending the model proposed by Werning (2015) with type-specific countercyclical employment risk. Households can be either employed ($\epsilon_t^i = 1$) or unemployed ($\epsilon_t^i = 0$). Define the type-specific employment rate as $e_t^i = \mathbb{E}\epsilon_t^i$. Aggregate earnings can thus be characterized by:

$$Y_t = \sum_{i \in I} \mu^i \left[e_t^i \bar{y}_i Y_t^{\psi^i} + \left(1 - e_t^i\right) \underline{y}_i Y_t^{\psi^i} \right] \tag{10}$$

where we assume that household income follows aggregate income according to $y_t^i(s_t) = \bar{y}_i Y_t^{\psi^i}$ for the employed and according to $y_t^i(s_t) = \underline{y}_i Y_t^{\psi^i}$ for the unemployed. The parameter ψ^i is the elasticity of income with respect to the aggregate, conditional on not changing employment states. Employment by type evolves according to a type-specific separation rate $\delta^i(Y_t)$ and job-finding rate $f^i(Y_t)$:

$$e_t^i = \left(1 - \delta^i(Y_t) \left(1 - f^i(Y_t)\right)\right) e_{t-1}^i + f^i(Y_t) \left(1 - e_{t-1}^i\right) \tag{11}$$

where the timing is such that we allow for households that lose their job to find one immediately within the period.

5.1.2 The dynamics of aggregate demand

In traditional macroeconomic models with a representative household or complete markets, the dynamics of aggregate demand are characterized by the dynamic optimality condition, or Euler equation, for aggregate consumption. With incomplete markets and idiosyncratic risk, there is typically no such condition. To characterize the effect of heterogeneous incidence on aggregate demand in a transparent way, we follow Werning (2015) and consider the zero-liquidity limit of the economy (where there is no asset trade in equilibrium), which allows the individual optimality conditions to be aggregated to a condition for aggregate consumption demand that is similar to the representative household's Euler equation in the absence of heterogeneity. In particular, as originally discussed in Krusell et al. (2011), the Huggett (1993) economy with the tightest borrowing limit ($B^i_t(s_t, Y_t) = 0 \; \forall t$) generates a well defined stochastic discount factor for the economy. The agent with the strongest incentive to save is the one who prices the risk-free bond.[17] In our setting, it is clear that one of the employed agents will be this 'marginal saver' (since unemployed agents have positive expected income growth and would thus like to borrow). The first-order condition for employed agents is given by:

$$\begin{aligned} U'(\bar{y}^i Y_t^{\psi^i}) \;&=\; \beta R_t \mathbb{E}_t \Bigg[\underbrace{\Big(1 - \delta^i(Y_{t+1}) \left(1 - f^i(Y_{t+1})\right)\Big) U'(\bar{y}^i Y_{t+1}^{\psi^i})}_{\text{remains employed}} \\ &\qquad + \underbrace{\delta^i(Y_{t+1}) \left(1 - f^i(Y_{t+1})\right) U'(\underline{y}^i Y_{t+1}^{\psi^i})}_{\text{becomes unemployed}} \Bigg] \end{aligned} \tag{12}$$

where the right-hand side equals the expected marginal utility across employment and unemployment states. The bond price is thus determined as:

$$\begin{aligned} 1 = \beta R_t \max_{i \in I} \mathbb{E}_t &\left[\frac{\left(1 - \delta^i(Y_{t+1}) \left(1 - f^i(Y_{t+1})\right)\right) U'(\bar{y}^i Y_{t+1}^{\psi^i})}{U'(\bar{y}^i Y_t^{\psi^i})} \right. \\ &\left. + \frac{\delta^i(Y_{t+1}) \left(1 - f^i(Y_{t+1})\right) U'(\underline{y}^i Y_{t+1}^{\psi^i})}{U'(\bar{y}^i Y_t^{\psi^i})} \right] \end{aligned} \tag{13}$$

Using the fact that $U'(c) = c^{-\sigma}$, and the in the aggregate $Y = C$, we can characterize the equilibrium.

Proposition 1. *In the economy we have the aggregate Euler relation:*

$$\hat{U}'(C) = \hat{\beta}(C') R \mathbb{E} \hat{U}'(C') \tag{14}$$

where $\hat{U}'(C) \equiv C^{-\sigma \psi_j}$, *where* $j = \arg\max$ *of the discount rate function* $\hat{\beta}$, *which is decreasing and given by:*

$$\hat{\beta} \equiv \beta \max_{i \in I} \Big((1 - \delta^i(C') + \delta^i(C') f^i(C')) + \delta^i(C')(1 - f^i(C')) U'(\underline{y}^i / \bar{y}^i) \Big)$$

[17] In principle, this provides only a lower bound for the equilibrium bond price, as at any higher price all agents would simply be constrained by the zero-borrowing limit. The equilibrium bond price is unique and equal to this bound, however, when there is an arbitrarily small supply of bonds.

Proof. Straightforward extension of Werning (2015) Proposition 4. □

Equation (14) characterises the dynamic response of aggregate consumption demand to shocks. In particular, two elements determine the response of C to any shock in the economy. First, as in standard representative-agent models, the elasticity of intertemporal substitution governs the aggregate response of consumption to an unexpected and purely temporary change in the real interest rate R. However, in contrast to the representative agent case, in our framework with (heterogeneous) unemployment risk, that elasticity depends on the responsiveness of individual incomes to aggregate income governed by ψ^j. If $\psi^j < 1$, the Euler relation implies that consumption is more elastic to the interest rate under incomplete markets than when markets are complete, as in Werning (2015). Effectively, the elasticity of intertemporal substitution rises from $\frac{1}{\sigma}$ to $\frac{1}{\sigma\psi^j}$. Intuitively, if earnings respond little to changes in aggregate output ($\psi \to 0$), changes in output must feed into earnings through the extensive margin, increasing risk.

The second element in equation (14) which determines the dynamics of aggregate demand is the discount factor $\hat{\beta}$ in (14), equal to the equilibrium change in current aggregate consumption C in response to a given change in future consumption C'. In our framework, $\hat{\beta}$ depends on the time-varying probability of staying employed. If this probability is pro-cyclical (as we show in Section 4.1), then the discount factor $\beta(C)$ is decreasing in aggregate consumption. As a result, contemporaneous consumption responds more than one for one to changes in future consumption, implying that changes to *future* interest rates have a greater effect on today's consumption than changes in the current interest rate.

5.2 Quantification

Equation (14) allows us to quantify the extent of amplification implied by incomplete markets using our empirical evidence for Germany. To do so requires estimates for 1) the elasticity of earnings conditional on staying employed by type ψ^i; 2) the ratio of the earnings of employed and unemployed by type $\underline{y}^i/\bar{y}^i$; 3) functions for the separation rate as a function of aggregate earnings by type $\delta^i(Y)$; and 4) functions for the job-finding rate as a function of aggregate earnings by type $f^i(Y)$. We focus on two types of households, $i = L, H$, corresponding to the top and bottom halves of the permanent income distribution.

We can measure ψ^i directly as the response of individual earnings to aggregate income $\beta_{12}^{q,E}$ for individuals employed in $t-1$ and $t+12$ in Figure 2. The low earnings types have $\psi^L = 0.42$ and the high earnings types $\psi^H = 0.52$ (see Table 2). As discussed in Section4.1, the heterogeneity in sensitivity of earnings conditional on being employed is small.

The ratio of earnings by type $\underline{y}^i/\bar{y}^i$ is set to be equal to 0.9 and 0.975 for low and high types, respectively, and captures the consumption fall upon unemployment (Kolsrud et al., 2018).[18]

Next, for $\delta^i(Y)$ and $f^i(Y)$ we log-linearize the functions, yielding

$$\delta^i(Y') = d_0^i + d_1^i \left(\log(Y') - \log(Y_{ss})\right) \tag{15}$$

$$f^i(Y') = f_0^i + f_1^i \left(\log(Y') - \log(Y_{ss})\right) \tag{16}$$

The estimates for d_0^i and f_0^i are based on the average separation rate into non-employment and job-finding rate from non-employment over the sample. The regression coefficients $\gamma_{12}^{q,E,U}$ and $\gamma_{12}^{q,U,E}$ in Figure 3—the effect of a one percent change in aggregate earnings induced by a monetary surprise on the probability of going from E to U and E to E—identify d_1^i and f_1^i, respectively. The estimates are summarized in Table 2.

Table 2: Parameter values

	(1) Low Type	(2) High Type	(3) Pooled
Consumption fall in unempl.	10%	2.5%	4%
MP effect on earnings of E to E (ψ^i)	0.42	0.52	0.49
MP effect on separations (d_1^i)	-1.01	-0.35	-0.64
Steady-state separations (d_0^i)	6.28%	2.48%	4.26%
MP effect on job-finding (f_1^i)	5.74	6.28	5.84
Steady-state job-finding (f_0^i)	27.68%	36.45%	28.69%
Derivative of discount factor ($\partial\hat{\beta}/\partial C'$)	-0.09	-0.009	-0.025

Note: The table shows the parameter values used in the different possible model calibrations. For details, see the text.

We study the effect of small shocks, implying small fluctuations in employment risk and earnings. Incentives to save for the employed are thus mainly governed by the average (or 'steady-state') probability to move to unemployment d_0^i, which is highest for low-income individuals (see Table 1). L type households are thus the marginal savers that determine the equilibrium dynamics of aggregate demand via equation (14). The effective elasticity of intertemporal substitution in the Euler relation is given by $\frac{1}{\psi^L\sigma} \approx 2.4 \times \frac{1}{\sigma}$, implying that consumption is more than twice as elastic to interest rates, compared to a framework with

[18] We are unaware of any studies that estimate a heterogenous drop in consumption upon unemployment for Germany, so here we rely an estimates from Sweden, that has similar social insurance systems. The heterogeneity is also consistent with evidence documented in Graves (2020) in the US.

complete markets or a representative agent. Thus, incomplete markets generate substantial amplification of the response of consumption to contemporaneous interest rate changes.

In addition to the higher effective EIS, the presence of cyclical separation risk implies that the effective discount factor $\hat{\beta}$ in the Euler relation will be decreasing in aggregate earnings. Differentiating the log-linearized expression in Proposition 1 and using $C = Y$ yields:

$$\frac{\partial \hat{\beta}}{\partial C'} = \beta \left(\left[\frac{\underline{y}^L}{\bar{y}^L} \right]^{-\sigma \psi^L} - 1 \right) (d_1^L - d_0^L f_1^L - d_1^L f_0^L - 2 d_1^L f_1^L dC'). \tag{17}$$

Assuming a standard value in macro for the EIS of 1/2 ($\sigma = 2$) yields $\frac{\partial \hat{\beta}}{\partial C} = -0.09$. Future increases in aggregate consumption induce more than a one-for-one movement in aggregate consumption today. To first order, a one percent increase in consumption in the next period would lead to a 1.1% increase in consumption today. This provides a sufficient statistic for the extent of demand amplification as a result of market incompleteness and heterogeneous incidence of cyclical earnings risk.

5.2.1 Pooled risk counterfactual

Past research (Auclert, 2019; Patterson et al., 2019) has focused mostly on the unequal incidence of level earnings changes, but not on the unequal incidence of *risk* across the distribution. Our empirical findings highlight that the incidence of earnings changes conditional on being employed is homogeneous across the earnings distribution (0.42 for the bottom half, 0.52 for the top half, and a pooled estimate of 0.49). Therefore, the unequal incidence in earnings is driven by the unequal incidence of the risk of moving out of employment. The first fact implies that heterogeneous incidence does not affect the elasticity of substitution much beyond the effect of cyclical individual earnings per se. The dynamics of the discount factor $\hat{\beta}$, in contrast, are substantially changed by heterogeneous incidence. In particular, the more cyclical unemployment risk of L types increases the cyclicality of demand through this channel.

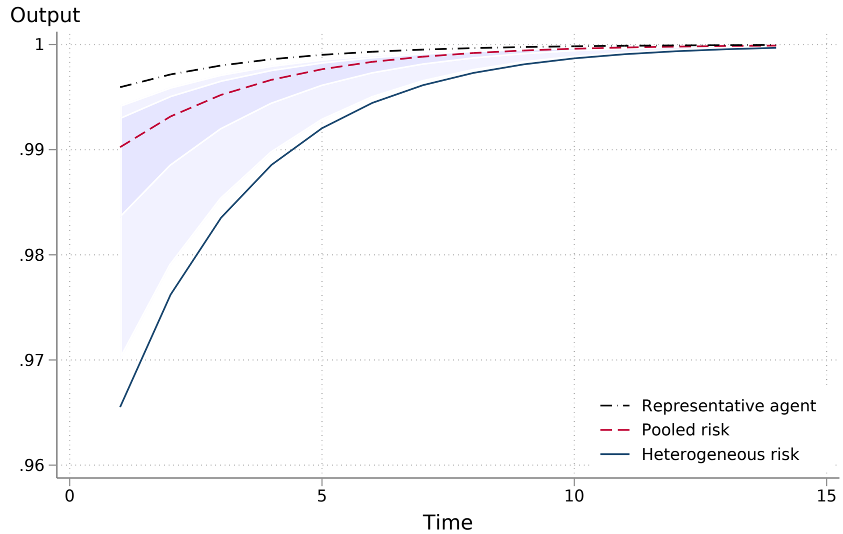
One way to highlight the importance of this unequal incidence of risk is to compute the Euler relation from Proposition 1 based on pooled data (i.e., without heterogeneous types based on past earnings). The coefficients for that experiment are in Column 3 of Table 2. The effective increase in the EIS is lower in the pooled version (increasing by a factor of 2 vs 2.4 in the heterogenous case). Second, the derivative of the discount factor with respect to aggregate consumption is about 70% smaller ($\frac{\partial \hat{\beta}}{\partial C} = -0.025$ as opposed to -0.09). Thus, ignoring the unequal incidence of risk would imply significantly less demand amplification to interest rates and future consumption.

5.2.2 Impulse responses

We illustrate the amplification results outlined above by computing the impulse response to a persistent monetary policy shock for the different cases. We decompose the response of consumption into channels driven by cyclical unemployment risk and its heterogeneous incidence. We compare three versions of the model, one with heterogeneous risk as in the data, one with homogeneous risk, and one with perfectly insured idiosyncratic risk. First, we set the real interest rate in Equation (14) equal to its average value in the data (2.4%). Then we compute the steady-state discount factors β necessary to solve the Euler equation under heterogeneous and pooled risk. We obtain $\beta_{het} = 0.965$ and $\beta_{pool} = 0.973$. Into each of the two economies, we introduce a monetary policy shock of 25 basis points that decays following an AR(1) process with a persistence of 0.7.

Figure 7 shows the impulse responses to this shock in heterogeneous and pooled risk cases, as well as the representative agent case (with perfectly insured idiosyncratic risk). The representative-agent economy experiences the smallest initial drop in aggregate output: less than 50 basis points. In the pooled-risk economy, output drops by slightly less than one percentage point on impact, as the rise in unemployment risk contracts consumption demand by more than in the representative-agent case. The impulse response in the economy with the heterogeneous incidence of risk further amplifies the drop in consumption on impact up to 3.5 percentage points. Thus, accounting for the heterogeneous incidence of monetary policy on unemployment risk yields significantly larger output responses. We quantify the uncertainty around these impulse responses implied by the estimates in Table 2 using a boot-strap procedure. The responses in the heterogeneous-risk model are significantly stronger than those in the homogeneous-risk counterpart.

Figure 7: Model impulse responses



Note: The figure shows the impulse responses of output in the representative agent economy (dash-dotted line), the economy with the homogeneous incidence of unemployment risk (dashed line), and the one with the heterogeneous incidence to a monetary policy shock (solid line). The shaded areas indicate 68 and 90 percent confidence intervals calculated using a boot-strap procedure. The shock raises the real interest rate by 25 basis points and then follows an AR(1) process with persistence of 0.7. For more details on the respective models and their calibration, see the text.

6 Conclusion

Monetary policy surprises affect income growth substantially more at the bottom of the earnings distribution. This heterogeneous incidence is mainly driven by the response of separation rates for the poor. Job-finding rates and earnings growth of the employed are both procyclical, but with little differences across the distribution. While our findings are for Germany, we believe that they are most likely applicable more broadly. First, the heterogeneous incidence of risk is apparent for all changes in aggregate earnings (not just monetary surprises). Second, a larger elasticity of earnings of the poor has been documented across a large number of countries. Thus, it is reasonable to conclude that the mechanism that drives that larger elasticity in Germany is likely at play in other industrialized economies.

Using a general incomplete-markets setting with type-specific cyclical unemployment risk, we showed how the concentration of movements in separation risk among high-risk workers amplifies aggregate-demand responses to interest rate changes by making precautionary savings more volatile. Based on our estimates, this makes consumption more than twice as responsive to interest rates as would prevail under complete markets, and substantially more responsive than in a model with homogeneous risk.

Our work suggests that the burgeoning HANK literature needs to take the documented heterogeneity seriously in employment dynamics across the income distribution and that it should incorporate it explicitly into its analyses. Our findings also suggest that studying policies that aim to reduce this heterogeneous income risk can significantly reduce aggregate fluctuations. One step in that direction is understanding the mechanisms through which monetary policy generates heterogenous income risks—Moser et al. (2021) make progress along this dimension using similar data. We leave the study and design of such policies for future work.

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Appendix

A Micro data

We use the Sample of Integrated Labor Market Biographies (SIAB) data. The SIAB data is provided in the form of labor market spells, each at most one year in duration, reporting the average daily wage during the spell. We convert these spells into monthly observations and multiply the daily wages by 30 in order to ascertain monthly earnings. If an individual reports multiple simultaneous spells during a month, we keep the spell that is classified as "Subject to social security without special characteristics" (as classified in Table A4 of Ganzer et al. (2017)). If one of the simultaneous spells implies non-employment, we keep that spell and classify the individual as non-employed. We classify individuals who earn less than the lower social security contribution limit as non-employed. All non-employed workers are coded to have zero income.

We classify as unemployed those individuals who receive unemployment benefits (ALG). Because the definition and eligibility of these benefits changed over time, we declare any individuals who are non-employed but started their non-employment spell in unemployment as unemployed for the whole duration of the non-employment spell. This addresses in particular the shortening of unemployment benefit eligibility around 2005. All earnings are deflated into real earnings using the monthly CPI index obtained from the OECD.

B Additional results

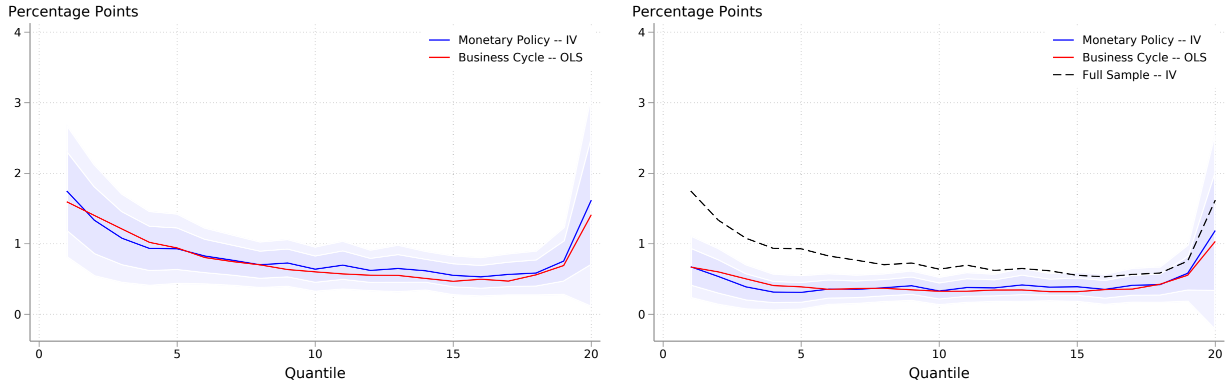
B.1 Results including unemployment benefits

In the main analysis, we investigate the effect of monetary policy surprises on labor earnings growth. To that end, we set labor earnings to zero for individuals who are non-employed in period t. However, our dataset contains some information about unemployment benefit receipts. We can thus investigate, to a certain extent, the effect of monetary policy on income including transfers, similar to Amberg et al. (2022). For individuals who are non-employed but do not receive benefits, we set their income to zero. We do not recompute aggregate earnings growth (used to compute the red-lines in the figures), in order to retain comparability with the main results.

Figure 8 reports the results from the robustness exercise, analogous to Figure 2 in the paper. Monetary policy surprises still affect the bottom of the distribution the strongest, but the effect is somewhat muted. This brings the overall effect (black dotted line in the right panel) closer to the earnings changes of individuals who remain employed. Naturally, the blue and red lines in the right panel remain unchanged, as they do not contain earnings received in unemployment.

Thus including unemployment benefits, to the extent that we have information on them, does not alter our conclusions that (i) the earnings growth of individuals at the bottom of the permanent income distribution is most affected by monetary policy surprises and (ii) the main reason for the heterogeneity is extensive margin transitions.

Figure 8: Regression coefficients β_{12}^{q} across the income distribution

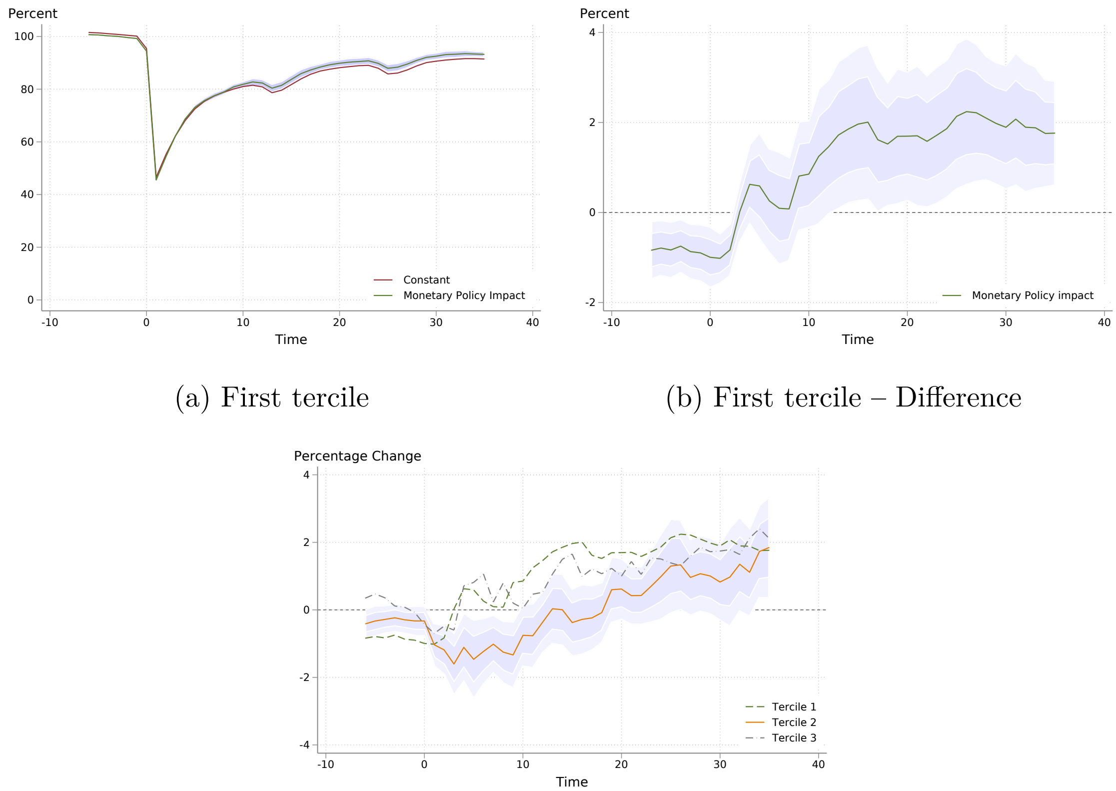


(a) Full sample (b) Only individuals employed in $t-1$ and $t+12$

Note: The *Left Panel* plots the coefficients β_{12}^{q} in Equation (2) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings) and $\beta_{Y,12}^{q}$ in Equation (3), separately for individuals who shared the same ventile of the permanent income distribution in period $t-1$. Income growth is computed as the log-change in the average income of individuals who were in the same ventile at time $t-1$. In unemployment, earnings are set to unemployment benefits if the individual receives any, otherwise they are set to zero. The *Right Panel* compares the coefficients β_{12}^{q} for the full sample in a ventile (gray dashed line) to $\beta_{12}^{q,E}$ and $\beta_{Y,12}^{q,E}$, estimated on a smaller sample of individuals who are employed both in period $t-1$ and $t+12$ (the blue and red lines, respectively). Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.

A smiliar exercise can be conducted regarding the longer-run earnings effects of unemployment, as in Section 4.2. Specifically, we can substitute the benefit income for the zero-earnings assumption used in that analysis. The top left panel in Figure 9 shows the results of this exercise. The fall in earnings upon unemployment is much less pronounced. Whereas before, earnings fell close to zero upon unemployment, the fall is now closer to 40 percent. However, as the top right panel shows, monetary policy still has a significant impact on earnings. After a year, earnings of individuals who lose their employment during periods of accommodating monetary policy have recovered on average about two percent more than those who become unemployed in normal times. These effects are similar to those for the other two terciles, plotted in the bottom panel of the same figure.

Figure 9: Effect of monetary policy on post-benefit earnings after unemployment



(a) First tercile

(b) First tercile – Difference

(c) Earnings (incl. UI)

Note: The *Left Panel* shows the average earnings, including unemployment benefit receipts, of individuals in the first tercile who transition into unemployment in month $t = 0$, relative to those who don't (red line). The green line shows how relative earnings change after a monetary policy surprise (scaled to be consistent with a one-percent increase in aggregate earnings). The shaded area indicates the 90 percent confidence band based on HAC standard errors. The *Right Panel* isolates the effect of a monetary policy surprise on the relative earnings, i.e. the difference between the two lines. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC standard errors. The *Bottom Panel* shows the effect of the same monetary policy surprise on relative earnings including unemployment benefit receipts. The dashed green lines represent estimates for the first tercile, the solid yellow lines those for the second and the dash-dotted grey line those for the third. The shaded areas represent 68 and 90 percent confidence bands based on HAC standard errors for the second tercile. Terciles are constructed based on average earnings during the five years prior to the start of the unemployment episode in period 0, conditional on gender and five-year age brackets. The sample period is 2000-2013.

B.2 Alternative measure of permanent income

In our baseline estimation, we sort individuals into quantiles based on their average earnings over the five year period preceding the monetary policy shock. This is our preferred measure of permanent income. A potential concern with this approach is that a five-year period is not long enough to accurately proxy for permanent income. In this case, some of the variation in our permanent income measure would be driven by temporary income fluctuations. In this section, we reproduce our main results for an alternative measure of permanent income: the fixed effect in a Mincer regression.

We estimate the following specification for all employed individuals in our sample:

$$\log(earn_{i,t}) = \alpha + \lambda_i + \beta_{ea} age_t + \beta_{eb} age_t^2 + \varepsilon_{i,t,ea} \tag{18}$$

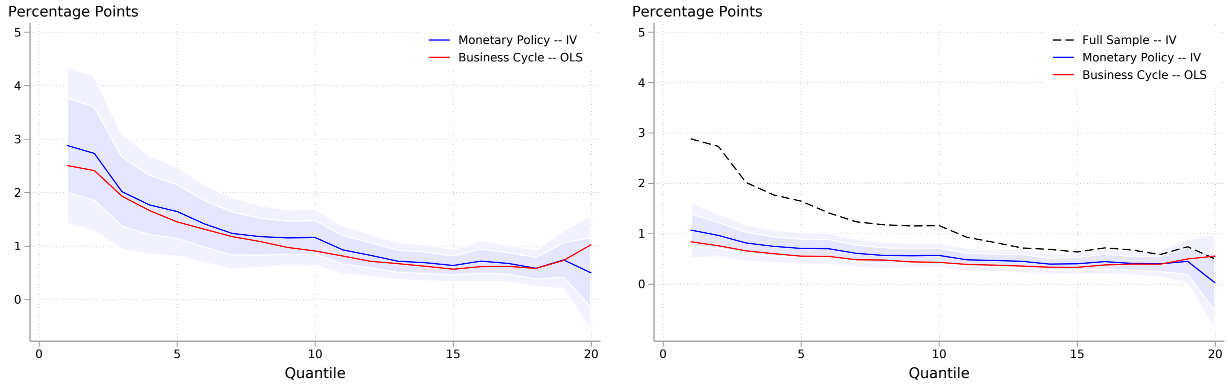
where age_t and age^2 represent a second order polynomial of individual i's age and λ_i is the earnings fixed effect for individual i, our proxy for lifetime earnings. Subsequently, each month, we sort all individuals into twenty quantiles based this measure.[19]

Figure 10 reports the results from this exercise, similarly to 2 in Section 4.1 of the paper. As in the baseline specification, the monetary policy surprise consistent with raising aggregate earnings by 1 percent affects the bottom end of the permanent income distribution significantly more than the top. If anything, the downward slope is slightly more pronounced in Figure 10. The increase in the effect at the top of the distribution observed in Figure 2, in contrast, is absent here. As before, the results appear to be driven by extensive margin transitions: the effect of monetary policy shocks on earnings is essentially homogeneous across the income distribution for individuals who remain employed. The effect of monetary policy surprises on labor market transitions (not reported here) are similarly close to those reported in Figure 3.

From the analysis in this section we conclude that our results are robust to the use of other measures of permanent income.

[19]When estimating the regression in Equation 18, we include all employed individuals in our dataset, including those whose earnings exceed the social security contribution cutoff. However, when computing the effect of monetary policy surprises on earnings growth, we again exclude the censored earnings observations.

Figure 10: Regression coefficients β_{12}^{q} across the income distribution



(a) Full sample

(b) Only individuals employed in $t-1$ and $t+12$

Note: The *Left Panel* plots the coefficients β_{12}^{q} in Equation (2) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings) and $\beta_{Y,12}^{q}$ in Equation (3), separately for individuals who shared the same ventile of the permanent income distribution in period $t-1$. Income growth is computed as the log-change in the average income of individuals who were in the same ventile at time $t-1$. The *Right Panel* compares the coefficients β_{12}^{q} for the full sample in a ventile (gray dashed line) to $\beta_{12}^{q,E}$ and $\beta_{Y,12}^{q,E}$, estimated on a smaller sample of individuals who are employed both in period $t-1$ and $t+12$ (the blue and red lines, respectively). **Ventiles are constructed based on the individual fixed effect λ_i in regression 18.**The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.

B.3 Results using different measures of monetary policy surprises

A potential shortcoming of the monetary policy surprises reported in Almgren et al. (2022) is that they may conflate two different components of monetary policy announcements. Nakamura and Steinsson (2018) and Jarociński and Karadi (2020) argue that a larger than expected interest rate cut, for example, may not only be an expansionary monetary policy action, but a signal to markets that the central bank anticipates a larger than expected contraction in the future. In their paper, Jarociński and Karadi (2020) make an effort to separately identify this information shock content of the ECB's monetary policy announcements in addition to the pure monetary policy component. In this section, we aim to show that our conclusions are robust to using their measure of pure monetary policy surprises as the shock variable.

Importantly, when estimating the effect of monetary policy on output, Jarociński and Karadi (2020) use their measure directly and do not use it to instrument for the surprise content in interest changes. We follow the same approach. Thus, in Equation 2, we substitute for Δi and estimate the following regression using OLS:

$$\Delta \log(\overline{earn}^{q}_{t+h}) = \alpha_h + \beta^q_h S_{JK} + \theta X_t + \epsilon^q_{t+h} \tag{19}$$

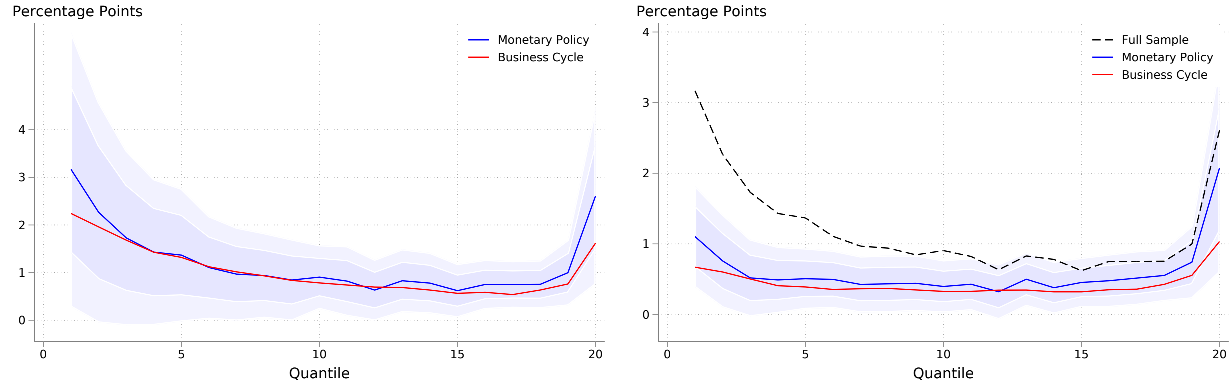
where S_{JK} is the monetary policy shock measure from Jarociński and Karadi (2020). For the estimation, we use the same control variables as in our main specification: three lags of Δi_t, aggregate earnings and S_{JK} as well as calendar month dummies.

Figure 11 reports the results. As in our main specification, monetary policy shocks have a larger effect at the low end of the aggregate income distribution. In fact, using the pure monetary policy component isolated in Jarociński and Karadi (2020), we find slightly larger effects on earnings, compared to the baseline. Again, the heterogeneity across the distribution is entirely driven by extensive margin transitions: the right panel of Figure 11 shows again homogeneous responses for employed individuals.

From this exercise we conclude that our results are robust to different identification schemes for monetary policy shocks.[20]

[20] We have also estimated regression 2 using the monetary policy surprises in Altavilla et al. (2019) and the results, not shown here, are very similar.

Figure 11: Regression coefficients β_{12}^{q} across the income distribution



(a) Full sample

(b) Only individuals employed in $t-1$ and $t+12$

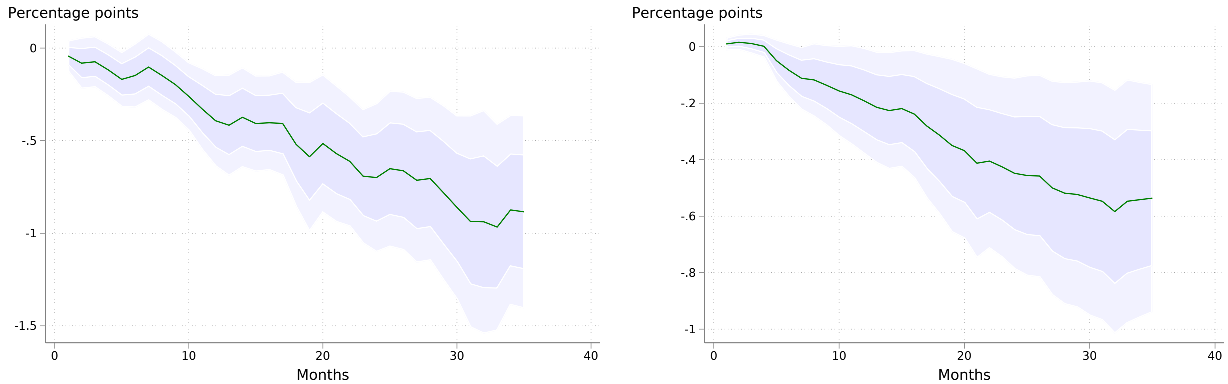
Note: The *Left Panel* plots the coefficients β_{12}^{q} in Equation (2) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings) and $\beta_{Y,12}^{q}$ in Equation (3), separately for individuals who shared the same ventile of the permanent income distribution in period $t-1$. Income growth is computed as the log-change in the average income of individuals who were in the same ventile at time $t-1$. **For this exercise, we substitute our measure of monetary policy surprises with the one proposed by Jarociński and Karadi (2020).** The *Right Panel* compares the coefficients β_{12}^{q} for the full sample in a ventile (gray dashed line) to $\beta_{12}^{q,E}$ and $\beta_{Y,12}^{q,E}$, estimated on a smaller sample of individuals who are employed both in period $t-1$ and $t+12$ (the blue and red lines, respectively). Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.

B.4 Impulse responses of sample aggregates

Figure 12 plots the impulse responses for aggregate earnings and the aggregate employment rate (as a percentage of fully attached individuals) as implied by our sample. The left panel plots the coefficient β^{h} in Equation 2 where the variable on the left-hand side is average earnings across all individuals, by month. In response to a one-standard-deviation monetary policy surprise, aggregate earnings fall by 0.2 percent by the end of the first year after the shock. The right panel plots the same estimation for the average employment rate. In response to a one-standard-deviation surprise, average employment falls by about 0.2 percentage points by the end of the first year after the shock.

Both figures are in line with the aggregate responses reported in Figure 1: a surprising contraction in monetary policy depresses economic activity and decreases aggregate earnings and aggregate employment.

Figure 12: Aggregate impulse responses



(a) Regression coefficients β_h for the full sample (b) Regression coefficients γ_h for the full sample

Note: The *Left Panel* plots the coefficients β_h in Equation (2) for aggregate earnings in the full sample, scaled by a one-standard-error contractionary monetary policy surprise. The *Right Panel* plots the coefficients β_h for the average employment rate in the sample. The shaded areas represent 68 and 90 percent confidence bands based on HAC standard errors, The sample period is 2000-2013.

B.5 Impulse responses by decile

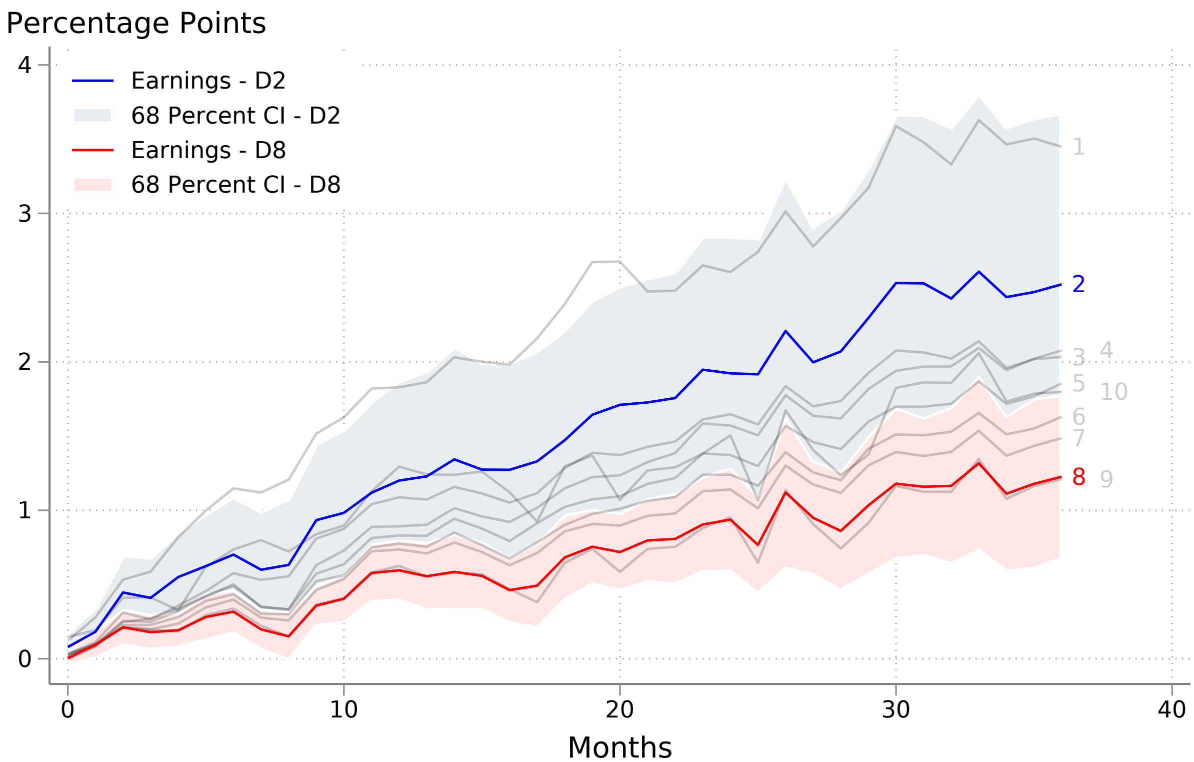
In addition to the aggregate impulse responses, Figure 13 reports the earnings impulse responses by quantile. In order to not clutter the figure too much, we conduct this exercise using deciles, as opposed to the ventiles in the main analysis. Moreover, we only report confidence intervals for deciles two and eight. These impulse responses are also highlighted in blue and red, respectively. All other impulse responses are displayed in grey.

The figure shows that the pattern observed at the 12-month horizon is consistent even at longer horizons: at the bottom of the permanent income distribution, monetary policy has a stronger effect on earnings growth compared to the top. In fact, the difference increases over time, such that two years after the shock, earnings growth is about 0.2 percentage points lower for the second decile, compared to the eighth.

B.6 Decomposition of the extensive margin

In section 4.1, we show the effect of monetary policy surprises on aggregate mean earnings by quantile, as well as the effects on a restricted sample of individuals who are employed in periods $t-1$ and $t+12$. We assert that the difference between the two effects must be driven by extensive margin transitions from or into unemployment. In this section, we investigate this pattern further, documenting the effect of monetary policy on the components of earnings growth along the extensive margin. Importantly, $\Delta \log(\overline{earn}^q_{t+12})$ cannot be defined for,

Figure 13: Regression coefficients β_h^d by decile d



Note: The figure plots the coefficients β_h^d in Equation (2), in response to a one-standard-error contractionary monetary policy surprise. Here, d represents deciles, as opposed to the 20 quantiles q in the main analysis. Each line represents the impulse response of a different decile, with the second decile highlighted in blue and the eighth decile highlighted in red. The shaded areas represent 68% confidence intervals.

individuals who are employed (unemployed) in period $t-1$, but unemployed (employed) in period $t+12$. However, we can separately investigate the effects of monetary policy on overall employment by quantile, exit-earnings of separators $(t-1)$ and starting-earnings job-finders $(t+12)$, respectively.

In order to document the effect of a monetary expansion on employment by quantiles, we estimate Equation 2, while substituting the log change in average employment for the log change in average earnings on the left-hand side. This is the second component in equation 4. The top panel in Figure 14 shows the results of this exercise. At the bottom of our income distribution, employment rises by about two percentage points, while towards the top, employment is almost unchanged. As our main exercises in section 4.1, these results imply that monetary policy affects the low end of the income distribution more strongly than the top, although our estimates are imprecisely estimated in the exercise at hand.

To quantify the effect of a monetary policy surprise on the earnings of separators or job-finders, we estimate the following specification:

$$\log(\overline{earn}^{q,\tau}_{t+12,t-1}) = \alpha_h + \beta^{q,\tau}_h \Delta i_t + \theta X_t + \epsilon^q_{t+h} \tag{20}$$

where $\overline{earn}^{q,\tau}_{t+12,t-1}$ represents the average earnings of all individuals in quantile q experiencing labor market transition $\tau \in \{E \to U; U \to E\}$ between periods t and $t+12$. As before, Δi represents changes in the ECB's policy rate which we instrument for as described in section 4.1; and X_t is the vector of controls variables.

The bottom left panel of Figure 14 displays the log of the average earnings observation in period $t-1$ for individuals who transition from employment to unemployment by period $t+12$. The negative estimates for $\beta^{q,E\to U}$ imply that those individuals who separate during the year after an expansionary monetary policy shock have lower earnings than those who separate in other periods. The effect is strongest at the bottom of the distribution. This result is in line with the top left panel of Figure 3, which indicates that separation rates (the complement to the E-to-E rates reported in the Figure) fall most at the low end of the income distribution. Hence, those who separate after an expansionary shock are likely in the low tail of the earnings (or productivity) distribution.

The bottom right panel of Figure 14 reports the change in the log of average entry-earnings due to a monetary expansion, for those who transition from unemployment to employment. Entry-earnings appear to be dampened, implying that although job-finding rates increase homogeneously across the distribution (according to the top right panel in Figure 3), the bottom of the distribution appears to sacrifice earnings.

To foster a better understanding of these results, we take a longer-run approach and investigate how the earnings of individuals who become unemployed in period 0 evolve relative to the earnings of those who do not. This exercise is similar in spirit to the one conducted in section 4.4, however, here we condition on employment.

Figure 15 documents that, conditional on employment, the earnings difference between individuals who become unemployed in period 0 and those who do not is larger after an expansionary monetary policy regime. Still, Figure **??** documents that an expansion has positive effects on re-employment probabilities for those who become unemployed in period 0 (left panel), and that these appear to dominate the conditional earnings effects documented below (middle panel)

B.7 Significance of differences across quantiles

From Figure 2, it is difficult to ascertain whether the impact of monetary policy is significantly different across quantiles. In this section, we report the t-statistics for such a test across all combinations of quantiles.

Table 3 reports the results for a test that investigates whether two quantile-specific coefficients are equal, i.e., the difference between them is zero. As the t-statistic grows, so does the likelihood that the null hypothesis is rejected.

The most significant differences can be observed between the first quantile and those above the median of the income distribution. As we move up the income distribution, the hypothesis of equality between two coefficients is less likely to be rejected; e.g., the coefficient reported for the third quantile is significantly different from coefficients for all quantiles between the 14th and 18th at the 68% significance level. At the same time, coefficients reported for the 16th quantile are singificantly different from those reported for the first seven quantiles as well as the last, at a significance level of 68%.

B.8 The impact of stayers

In Figure 2, to quantify the impact of the extensive margin on the effects of monetary policy, we restrict the sample to individuals who are employed in periods $t-1$ and $t+12$. This analysis conflates the effects of monetary policy on the earnings of job-switchers (those who are employed in t and $t+1$, but not continuously at the same employer) and job-stayers (those with the same employer throughout the time between $t-1$ and $t+12$).

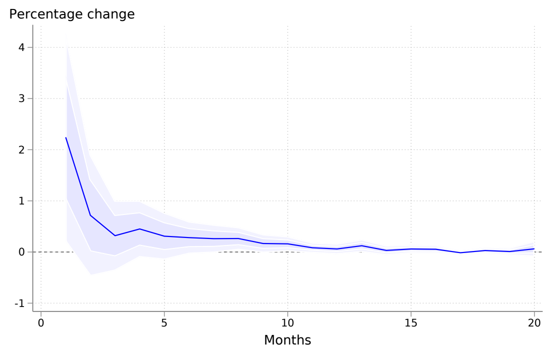
Figure 16 shows that this distinction is not meaningful in our context. The red line represents the effect of a monetary policy surprise on individuals who are employed in $t-1$ and $t+12$, the blue line restricts the sample further, to individuals who are job-stayers. The two lines are very close together, insignificantly different, and almost indistinguishable. The

Table 3: Test for difference of quantile-specific coefficients

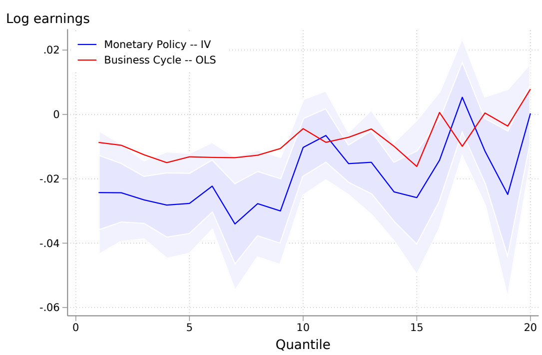
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20
Q1	0.00																			
Q2	-0.62	0.00																		
Q3	-0.96	-0.32	0.00																	
Q4	-1.14	-0.50	-0.19	0.00																
Q5	-1.11	-0.46	-0.13	0.07	0.00															
Q6	-1.33	-0.69	-0.39	-0.21	-0.30	0.00														
Q7	-1.43	-0.81	-0.53	-0.36	-0.46	-0.18	0.00													
Q8	-1.58	-0.98	-0.73	-0.59	-0.70	-0.45	-0.28	0.00												
Q9	-1.53	-0.92	-0.66	-0.51	-0.62	-0.36	-0.18	0.11	0.00											
Q10	-1.69	-1.11	-0.89	-0.78	-0.90	-0.69	-0.53	-0.26	-0.37	0.00										
Q11	-1.60	-1.00	-0.76	-0.62	-0.74	-0.49	-0.33	-0.05	-0.16	0.21	0.00									
Q12	-1.75	-1.18	-0.97	-0.88	-1.01	-0.82	-0.67	-0.40	-0.51	-0.13	-0.34	0.00								
Q13	-1.71	-1.14	-0.93	-0.82	-0.95	-0.74	-0.59	-0.32	-0.43	-0.06	-0.27	0.06	0.00							
Q14	-1.76	-1.20	-1.00	-0.91	-1.04	-0.85	-0.70	-0.43	-0.55	-0.15	-0.38	-0.02	-0.09	0.00						
Q15	-1.89	-1.36	-1.19	-1.14	-1.29	-1.15	-1.02	-0.78	-0.90	-0.51	-0.72	-0.41	-0.45	-0.40	0.00					
Q16	-1.92	-1.38	-1.23	-1.18	-1.33	-1.20	-1.08	-0.85	-0.96	-0.58	-0.79	-0.48	-0.51	-0.47	-0.07	0.00				
Q17	-1.90	-1.37	-1.20	-1.15	-1.30	-1.17	-1.04	-0.80	-0.92	-0.54	-0.75	-0.44	-0.47	-0.43	-0.03	0.04	0.00			
Q18	-1.87	-1.33	-1.16	-1.09	-1.24	-1.09	-0.96	-0.72	-0.83	-0.45	-0.66	-0.35	-0.39	-0.34	0.05	0.12	0.08	0.00		
Q19	-1.64	-1.07	-0.83	-0.71	-0.83	-0.60	-0.45	-0.20	-0.30	0.03	-0.16	0.15	0.09	0.17	0.48	0.54	0.51	0.43	0.00	
Q20	-0.44	0.12	0.39	0.54	0.51	0.69	0.78	0.91	0.86	1.01	0.93	1.06	1.03	1.07	1.19	1.21	1.20	1.17	0.98	0.00

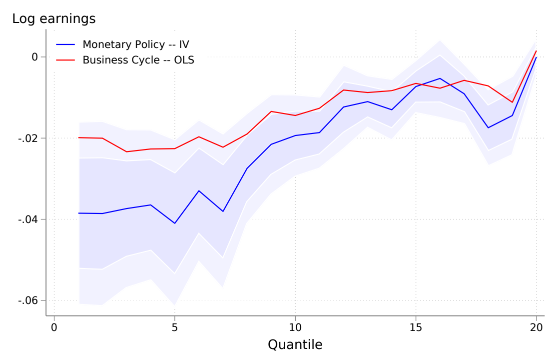
reason is that, in each quantile, the vast majority of individuals are job-stayers, conditional on being employed in $t-1$ and $t+12$. Thus, the earnings impact of job-switchers is low. Additionally, although more noisy, the earnings changes of job-switchers are similar to those of job-stayers (not shown).

Figure 14: Components of the extensive margin



(a) Change in share of employed workers



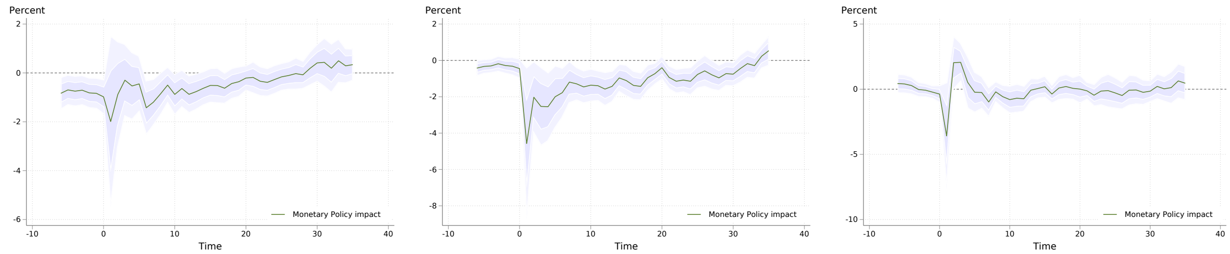


(b) Last earnings of separators

(c) First earnings of job-finders

Note: The *Top Panel* plots the coefficients β_{12}^{q} in Equation (2), where the left-hand side is the average employment rate by quantile. The *Bottom Left Panel* plots $\beta_{t-1}^{q,E\rightarrow U}$ from Equation 20 with Δi as the right-hand side variable, instrumented using our monetary policy instrument (blue) and using ΔY as the right-hand side variable (red). The *Bottom Right Panel* plots $\beta_{t+12}^{q,U\rightarrow E}$ from Equation 20 with Δi as the right-hand side variable, instrumented using our monetary policy instrument (blue) and using ΔY as the right-hand side variable (red). Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.

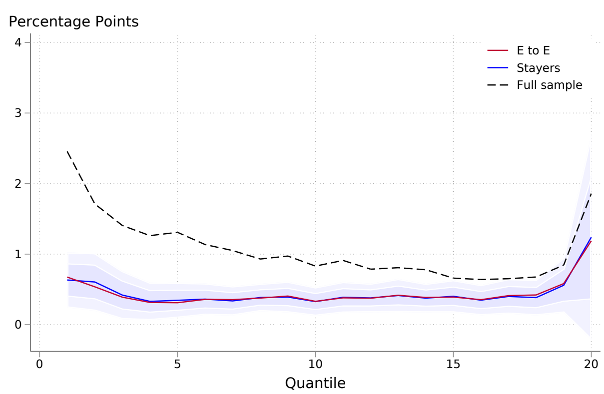
Figure 15: Conditional earnings effects of unemployment



(a) First tercile (b) Second tercile (c) Third tercile

Note: The figure shows the effect of a monetary policy surprise (scaled to be consistent with a one-percent increase in aggregate earnings), on the earnings of individuals who become unemployed in period 0 across terciles, relative to those who do not, **conditional on being employed**. The shaded areas represent 68 and 90 percent confidence bands based on HAC standard errors for the second tercile. Terciles are constructed based on average earnings during the five years prior to the start of the unemployment episode in period 0, conditional on gender and five-year age brackets. The sample period is 2000-2013. The *Left Panel* shows the effect in the first tercile. The *Middle Panel* shows the effect in the first tercile. The *Right Panel* shows the effect in the first tercile.

Figure 16: The impact of switchers on coefficients β_{12}^q



Note: The Figure plots the coefficients β_{12}^q in Equation (2) (scaled by an expansionary monetary policy surprise consistent with a one-percent increase in aggregate earnings), separately for individuals who shared the same ventile of the permanent income distribution in period $t-1$. It compares the coefficients β_{12}^q for the full sample across ventiles (gray dashed line) to $\beta_{12}^{q,E}$ and $\beta_{12}^{q,stay}$, estimated on a smaller sample of individuals who are employed both in period $t-1$ and $t+12$ and those who stay with the same employer for the same time (the blue and red lines, respectively). Ventiles are constructed based on average earnings during the five years prior to $t-1$, conditional on gender and five-year age brackets. The shaded areas indicate 68 and 90 percent confidence intervals based on HAC robust standard errors. The sample period is 2000-2013.