# The Curious Incidence of Monetary Policy Shocks Across the Income Distribution*

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**Abstract**

We use high-frequency administrative data from Germany to study the effect of monetary-policy shocks on incomes and employment prospects along the income distribution. We find that income growth at the bottom of the income distribution is substantially more affected by monetary policy shocks. Much of this heterogeneity comes from stronger effects of these shocks on the separation rates of the poor. In a workhorse Heterogeneous-Agent New Keynesian model such heterogeneous incidence substantially amplifies the aggregate effects of monetary policy interventions.

# 1 Introduction

Do monetary policy interventions affect poor workers' earnings and employment prospects more than those of the rich? Answering this question is important to assess the welfare effects of monetary policy, and thus for policy design. It is also important for the transmission of monetary policy shocks to aggregate demand, as the consumption of poorer households is likely to react more strongly to fluctuations in their incomes (Patterson et al., 2019), and because substantial heterogeneous responses of labor market risk may change the transmission of monetary policy (Ravn and Sterk, 2017; Werning, 2015).

We use a long panel of detailed administrative data from Germany, containing individual labor market biographies including earnings. The high frequency nature of our data allows us

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to estimate responses of earnings and transitions in employment status to monetary policy shocks, which we identify using high-frequency changes in Overnight Indexed Swap rates. We find that monetary policy shocks disproportionately affect the extremes of the income distribution. In particular, the response of average earnings to a monetary-policy shock is about three times as large at the bottom of the income distribution as the average. We find this heterogeneity in the response to monetary-policy shocks to be stronger than that in the unconditional comovement of individual and aggregate earnings (previously referred to as *worker betas*, Guvenen et al. (2017)).
Much of this heterogeneous incidence on individual earnings arises because monetary policy has stronger effects on the labor market prospects of poor workers, who experience a substantially stronger fall in separation risk after an expansionary monetary policy shock. We also document substantial, and strongly heterogeneous, effects of monetary policy shocks on the consequences of unemployment.

Our results seem important for understanding the transmission of monetary policy interventions to aggregate demand, for understanding their welfare effects, and for optimal policy design. In particular, when poorer individuals have higher marginal propensities to consume, the stronger incidence of monetary policy on their incomes that we find is a source of amplification not present in standard representative-agent models for monetary-policy analysis, including those typically used by central banks (Kaplan et al., 2018; Patterson et al., 2019). When idiosyncratic income shocks are imperfectly insured, an additional source of amplification arises because monetary policy makes income risk countercyclical, reducing unemployment risk and precautionary savings in booms (Rendahl, 2016; Werning, 2015). To the extent that precautionary savings increase with permanent income, however, our finding that monetary policy predominantly affects unemployment risk of the poor implies that this amplification may be smaller than suggested by simple models that abstract from heterogeneity in employment incomes (Bilbiie, 2020; Challe, 2020; Ravn and Sterk, 2017).
When insurance against individual income risk is imperfect, the heterogeneous incidence of policy and business cycles that we document is important for welfare analysis. When marginal propensities to consume decrease with permanent incomes, our results suggest that consumption of the poor is substantially more affected by monetary policy and business cycles than that of the rich. [The strong effects of monetary policy at the very bottom of the income distribution that we document deserve particular attention in this context.] While the individuals in the top decile of the permanent income distribution are also more strongly affected, they are likely better insured against income fluctuations.
Taken together, the amplification and welfare effects implied by heterogeneous incidence suggest that our results are important also for the design of optimal monetary policy. The

precautionary savings channel itself may warrant a substantially more active monetary policy stance to counteract countercyclical precautionary savings (Challe, 2020). Countercyclical income risk in response to monetary policy reinforces this, because stronger output stabilisation reduces idiosyncratic consumption fluctuations in recessions (when they are particularly costly, which makes the price of increased fluctuations in booms worth paying, Acharya et al. (2020)). The importance and heterogeneity of extensive-margin effects of policy on employment transitions that we find calls for an environment with both cyclical unemployment transitions and idiosyncratic risk in employment incomes for conducting policy analysis, as for example in Gornemann et al. (2016).

## Relation to the literature

A large literature empirically investigates the heterogeneous effects of business cycles on individual income risk using administrative datasets, see Guvenen et al. (2015, 2017) (US), Halvorsen et al. (2020) (Norway), Hoffmann and Malacrino (2019) ( Italy), De Nardi et al. (2019), (Netherlands and US). Our high-frequency dataset allows us to study the heterogeneous incidence of monetary policy shocks on earnings and employment transitions, and to quantify the difference with respect to the incidence of average business cycles.

We contribute more directly to a small empirical literature on the effects of monetary policy on inequality (Coibion et al., 2012). Holm et al. (2020) show that contractionary shocks reduced nonfinancial incomes, but most so at the bottom of the liquid asset distribution. We perform our analysis at monthly frequency, and look at the dynamic effects of monetary policy shocks on both earnings and labor market transitions. Moreover, we do this for the largest European economy, Germany. This makes it crucial to identify exogenous changes in interest rates, which we do using high-frequency changes in Overnight Indexed Swap rates.[1]

Our findings contribute to an empirical foundation for the large literature on the effect of aggregate shocks in economies with heterogeneity in wealth and income. Auclert (2019) shows that, in a large family of macroeconomic models[2], the elasticity of individual earnings to aggregate earnings is a crucial statistic in evaluating the effectiveness of monetary policy. Along similar lines, Werning (2015) and Ravn and Sterk (2017), among others[3], point to the importance of cyclical earnings *risk* as a crucial factor that governs the macroeconomy's response to aggregate shocks. We provide an empirical foundation for these studies, as we estimate both the elasticity of earnings and labor market transition probabilities (i.e. risk) along the distribution.

[1]See e.g. Gertler and Karadi (2015), Almgren et al. (2019)

[2]See e.g. Kaplan et al. (2018), Bilbiie (2020), Hagedorn et al. (2019)

[3]See e.g. Gornemann et al. (2016), Challe (2020)

The next section presents the data and desribes the structure of income and employment transitions in our sample on average. Section 3 describes how we identify monetary-policy surprises, and how we use them to study their heterogeneous incidence along the income distribution. Section 4 investigates the effects monetary policy shocks. Section 5 concludes.

## 2 Data

We use administrative social security data for about 1.7 million German individuals from the Sample of Integrated Employment Biographies (provided by the Research Data Center, FDZ). Our data covers the years between 1975 and 2014 (although most of our analysis starts in 2000), and excludes civil servants and self-employed individuals. Each observation in the dataset is a labor-market spell.[4] We convert these spells into monthly employment histories for each individual, resulting in about 300 million person-month observations. Each monthly observation includes an individual's employment status and average daily labor earnings, which we convert to monthly earnings.

Because we are interested in the effect of monetary policy on labor earnings and employment status of individuals, 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[5]) and the unemployed, defined as individuals who received unemployment benefits at the beginning of their current non-employment spell. An appendix provides detail on the sample and variable definitions, and describes how we deal with top-coding, and earnings observations below the social-security threshold.

We study the differences in the earnings response to monetary-policy shocks across the income distribution by ranking individuals in a given period according to a proxy measure of their *permanent* income. Our preferred proxy is average earnings over the five years preceding quarter $t$ as in Guvenen et al. (2017).[6] Using this measure, we construct quantiles for every month $t$, based on a time-varying sample that includes all individuals who are classified as employed or unemployed in months $t-1$ and $t+12$ (because we focus on 12-month earnings changes and unemployment transitions). We exclude individuals whose earnings observations are top-coded in both periods.

[4] 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).

[5] Marginal part-time workers are defined as those individuals who earn an income below the assessment floor for social security contributions.

[6] Due to the construction of permanent income, our sample is restricted to workers who have at least one earnings observation in the five years prior to period $t$. All non-employed workers are coded to have zero income.

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 |
| Female | 0.67 | 0.66 | 0.67 | 0.62 | 0.52 | 0.42 | 0.36 | 0.32 | 0.29 | 0.23 |
| Age | 40.23 | 41.50 | 42.41 | 42.26 | 42.02 | 42.70 | 43.59 | 44.44 | 44.94 | 45.81 |
| Education | 2.53 | 2.46 | 2.42 | 2.44 | 2.44 | 2.39 | 2.38 | 2.44 | 2.60 | 2.95 |
| Monthly earnings | 1290.92 | 1476.38 | 1678.45 | 1945.21 | 2222.38 | 2478.54 | 2751.54 | 3066.26 | 3477.48 | 4261.92 |
| Employed | 0.84 | 0.88 | 0.92 | 0.94 | 0.95 | 0.97 | 0.98 | 0.99 | 0.99 | 0.98 |
| Job finding | 0.33 | 0.44 | 0.51 | 0.52 | 0.55 | 0.58 | 0.54 | 0.59 | 0.55 | 0.50 |
| Job loss | 0.06 | 0.05 | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 | 0.01 | 0.01 | 0.02 |
| Observations | 29617 | 29617 | 29617 | 29620 | 29621 | 29619 | 29621 | 29619 | 29621 | 29621 |

**Note:** The table shows values of different variables averaged within deciles of the permanent income distribution in January 2010. Education takes a value of 1 for individuals without a degree, 2 for vocational training, 3 for high school, 4 for high school and vocational training, 5 for graduates of technical colleges and 6 for university graduates. We impute education following the imputation procedure 1 in Fitzenberger et al. (2005).

To understand how key variables evolve along the distribution of permanent incomes (henceforth simply the "income distribution"), Table 1 reports descriptive statistics within deciles of our permanent-income measure in January 2010.[7]

The gradient of nominal earnings across the distribution is substantial, with average earnings in the top decile more than 3 times higher than in the first. Employment rates are high in this sample of highly-attached individuals. They average 84 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 below one third in the bottom decile, but are roughly flat between 50 and 60 percent in the top three quartiles. Job-loss probabilities (similarly defined) fall monotonically, from 6 to 2 percent, across the distribution. Because 70 percent of the individuals in our sample indicate vocational training as their highest qualification, education levels are similar across the first 8 deciles, but strongly rise across the top two (where degrees from technical colleges and universities are more common). Importantly for our analysis, which abstracts from life-cycle heterogeneity, the mean age differs only modestly across the earnings distribution, with individuals in the top quintile only around three years older than the average age in the sample. Finally, the gradient of gender composition is substantial (with only 23 percent of women in the top permanent income decile in 2000).

[7]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).

# 3 Estimation strategy

This section describes how we identify monetary policy surprises, and how we estimate their effects on earnings and labor market transitions.

## 3.1 Identifying monetary policy surprises

We focus on the period between January 2000 and December 2012, when European monetary policy was conducted by the ECB.[8] Since the German economy accounts for roughly a quarter of Euro-area GDP, however, it is likely that ECB monetary policy is 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, we use high-frequency data on Overnight Index Swap (OIS) rates. We use this to construct an instrumental variable, $Z_t$, that captures unexpected changes in ECB policy in the following way[9]: 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 these two events in a narrow time window around them.[10] 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. We use $Z_t$ as an instrument for unexpected changes in the interest rate that the ECB charges for its main refinancing operations (MROs), which we denote as $\Delta i_t$.

## 3.2 Estimating the effects of a monetary policy surprise

Our aim is to estimate the effect of monetary policy surprises on earnings growth and probabilities of transition between different labor market states, separately for individuals in different quantiles of the permanent-income distribution. For this, we first define $Q$ quantile-samples, consisting of individuals whose permanent-income measure in period $t-1$ falls in quantile $q = 1, ..., Q$. For each of these quantile-samples, or subsamples defined by

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

[9] See (Almgren et al., 2019) for details

[10] We calculate the average rates in windows 15 minutes before and 30 minutes after the press release and the press conference. We take the difference between the pre- and post- window in each case and sum the two.

labor market status, we estimate two regressions, utilizing a local projections approach (Jordà, 2005). First

$$earn_{t+h} - earn_{t-1} = \alpha_h + \beta_h \Delta i_t + \theta X_t + \epsilon_{t+h} \quad (1)$$

where $earn_{t-1}$ and $earn_{t+h}$ denote the logarithms of average labor earnings in, respectively, periods $t-1$ and $t+h$ of individuals who belong to the same quantile in period $t-1$. The left-hand side of the equation thus equals the log-change in average real monthly earnings for individuals in a particular quantile between periods $t-1$, i.e. one period before the shock, and period $t+h$. We focus on two earnings measures, defined as averages across different subsamples within a given quantile of the permanent-income distribution. First, average labor earnings across all individuals in a quantile (including the unemployed, who have zero labor earnings), which we call *average labor earnings* and simply denote as $earn_s$; and second, the average *labor earnings of the employed* in period $s$, denoted $earn_s^E$.

The coefficient $\beta_h$ captures the effect on earnings growth between periods t and $t+h$ of a change in interest rates $\Delta i_t$ in period $t$ (instrumented by $Z_t$ to identify surprise changes as described above, following Stock and Watson (2018)). The vector $X_t$ contains calendar month dummies and lagged values of $\Delta i_t$ and $Z_t$. $\epsilon_{t+h}$ is an error term. Earnings are deflated using the Harmonized Index for Consumer Prices for Germany.[11] Note that, since the maximum length of an employment spell is twelve months, our main analysis of the percentage change in earnings between $t-1$ and $t+12$ includes earnings observation drawn from two different employment spells.

To study the effect of monetary policy on transitions in the labor market, we assign individuals every month to one of two labor market states: we define as *employed* those employees who are liable to social security contributions without special characteristics. This excludes interns, trainees and marginal part-time workers (Ganzer et al., 2017). As *unemployed*, we denote individuals who receive unemployment benefits (this definition is narrower than the actual unemployment rate). If an individual starts a non-employment spell as unemployed, according to our definition, we denote the whole spell as an unemployment spell, in order to tackle changing eligibility criteria for unemployment benefits.

Similarly to Equation (1), we then estimate the following regression separately for each quantile-subsample:

$$TR_{t+h}^{s_1,s_2} = \alpha + \gamma_h^{s_1,s_2} \Delta i_t + \theta X_t + \epsilon_{t+h} \quad (2)$$

where $TR_{v,t+h}^{s_1,s_2}$, indicates the share of individuals in labor-market state $s_1$ in period $t-1$ that

[11] Obtained from Eurostat, series prc_hicp_midx.

transit to $s_2$ in period $t+h$. $s_1$ corresponds to either employment ($s_1 = E$) or unemployment ($s_1 = U$), while for those employed in $t-1$ and $t+h$ ($s_1 = s_2 = E$) we also identify the subset of "switchers" who are employed in a different job in $t+12$ ($s_2 = switch$). The coefficient $\gamma_h^{s_1,s_2}$ thus measures the percentage point change in response to a monetary-policy surprise in the share of individuals in state $s_1$ that make a particular labor market transition, for a given quantile. Again, the vector $X_t$ contains calendar-month dummies and lagged values of $\Delta i_t$ and $Z_t$.

We compare the dynamic effect of monetary policy shocks captured by $\beta_h$ and $\gamma_h^{s_1,s_2}$, to an alternative measure that quantifies the comovement of individual earnings and transition probabilities with a measure of the business cycle more generally (as resulting from all shocks to the economy). Specifically, in the spirit of Guvenen et al. (2017), we use earnings averaged across all individuals in our sample (which we label *aggregate earnings*) as a proxy of the business cycle and estimate the two following regression:

$$earn_{t+h} - earn_{t-1} = \alpha_q + \beta_{Y,h}\Delta_h Y_t + \gamma X_t + \epsilon_{t+h} \tag{3}$$

$$TR_{t+h}^{s_1,s_2} = \alpha + \gamma_{Y,h}^{s_1,s_2}\Delta_h Y_t + \theta X_t + \epsilon_{t+h} \tag{4}$$

where $\Delta_h Y_t$ denotes the (log-) change in aggregate earnings between period $t+h$ and $t-1$.

# 4 The effect of monetary policy surprises on earnings and labor market transitions

This section reports our empirical results on the effect of monetary policy surprises. Our estimation sample comprises the period between 2000M1 to 2012M12.[12]

## 4.1 The effect of monetary policy surprises on aggregate variables

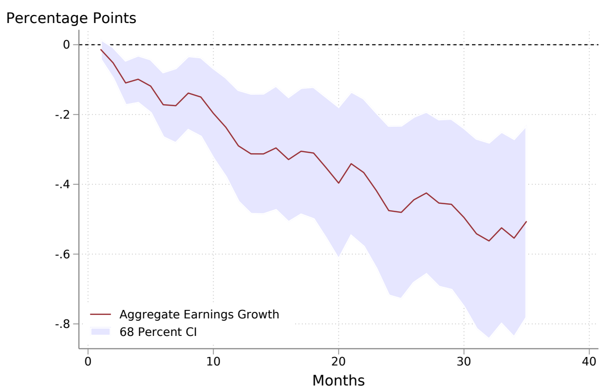
An appendix documents that the monetary-policy surprises we identify affect aggregate variables in line with what has been documented in previous studies (Almgren et al., 2019; Georgiadis, 2015). In particular, a contractionary monetary-policy surprise has little effect on inflation in Germany, but implies a persistent fall in output and a persistent rise in unemployment.

As a benchmark for the heterogeneous responses of individuals with different incomes that

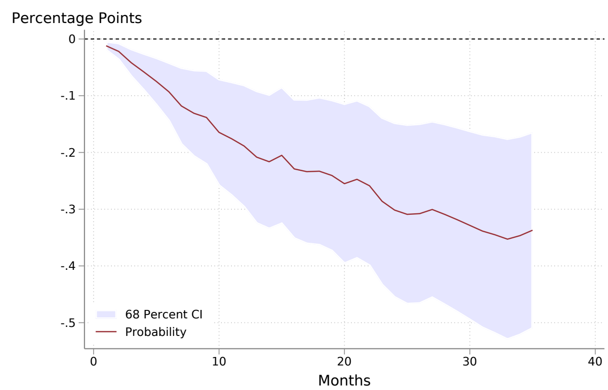
[12]We make use of data until 2014M12 to construct impulse responses, and since 1995 in order to compute our backward-looking permanent income measure, but only consider monetary policy surprises from 2000M1 to 2012M12.

we document below, Figure 1 shows the response of *aggregate* earnings (the average earnings across all individuals) and *average* employment transitions in our sample. Specifically, the figure plots the estimated coefficients $\beta_h$ and $\gamma_h^{EE}$ in (1) and (2), scaled by one-standard-error contractionary monetary-policy surprise, for the whole sample (so without allowing the coefficients to differ across ventiles of the permanent-income distribution). The left panel shows that the response of earnings to a one-standard-deviation contractionary monetary-policy surprise builds up gradually, reaching a point estimate of about 0.5 percentage points after two years. This reduction in average earnings comes with a substantial increase in transitions into unemployment (a fall in the probability of being employed), as documented in the right panel.

Figure 1: Aggregate Impulse responses




a) Regression coefficients $\beta_h$ for the full sample



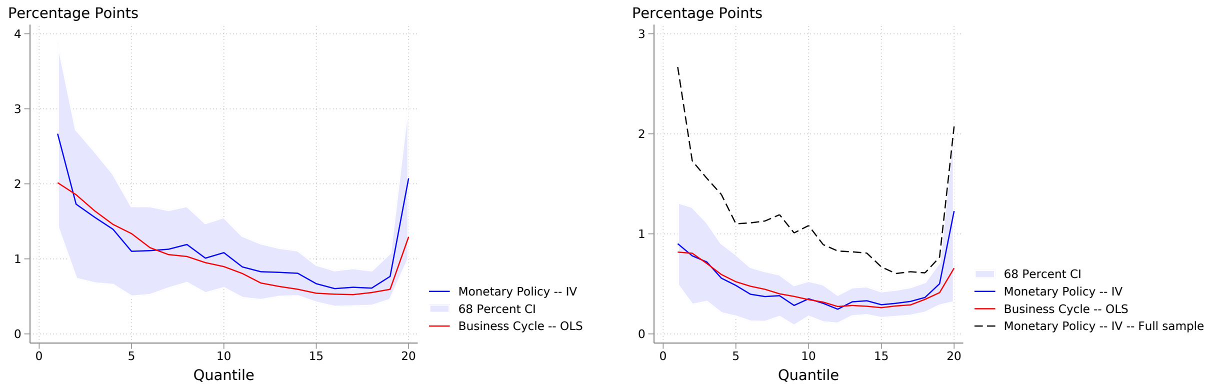

b) Regression coefficients $\gamma_h$ for the full sample

**Note:** Panel a) plots the coefficient $\beta_h$ in Equation (1), scaled by a one-standard-error contractionary monetary-policy surprise, estimated on the whole sample. Panel b) plots the coefficients $\gamma_h^{E,E}$ for individuals who transition form employment to employment ($s_1 = s_2 = E$), again for the whole sample. The shaded area indicates 68 percent confidence bands.

## 4.2 Monetary policy effects on earnings across the income distribution

This section shows that there is substantial heterogeneity in the response of individual earnings to monetary policy shocks across the distribution of permanent incomes. We focus on $\beta_{12}$, the 12-month response in Equation (1), which we estimate separately for each ventile of the distribution of our permanent-income proxy. We choose an expansionary monetary-policy surprise that implies a one-percent increase in *aggregate* earnings in our sample at the 12-month horizon. This allows us to compare the response of individual earnings to this expansionary monetary-policy surprise with $\beta_{Y,12}$, the response to an unconditional increase in average earnings of the same size in Equation (3).

Figure 2: Regression coefficients $\beta_{12}$ for ventiles of the income distribution




a)Full sample

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

**Note:** Panel a) plots the coefficients $\beta_{12}$ in Equation (1) (scaled by an expansionary monetary-policy surprise consistent with a one-percent increase in aggregate earnings) and $\beta_{Y,12}$ in Equation (3), separately for individuals who shared the same ventile of the permanent-income distribution in period $t$. Income growth is computed as the log-change in the average income of individuals who were in the same ventile at time $t$. Panel b) compares the scaled coefficients $\beta_{12}$ for all individuals in a ventile (gray dashed line) to $\beta_{12}$ and $\beta_{Y,12}$ when estimated on a smaller sample of individuals in a ventile who are employed both in period $t-1$ and $t+12$ (the blue line). The shaded area indicates 68 percent confidence bands for $\beta_{12}$ .

The point estimates of $\beta_{12}$ for the growth of average earnings of all indivduals in a ventile, the blue line in panel a) of Figure 2, show that there is a pronounced U shape in the response of earnings to monetary-policy surprises across the permanent-income distribution. In particular, earnings of the poorest individuals, in the bottom ventile, respond almost three times as much as aggregate earnings. Moving up the income distribution, this response declines strongly in magnitude, to about two thirds of the average effect in ventiles 15 to 19. Earnings of the income-rich, in the top ventile, again respond more, about twice as strongly as average earnings. The red line in Figure 2a depicts the point estimates $\beta_{Y,12}$, summarising the comovement of individual and aggregate earnings growth 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, but rises less in the extreme ventiles than the effect of monetary-policy surprises.

Because the estimates of $\beta_{12}$ depicted in the left panel of Figure 2 are based on the growth of average labor earnings of all individuals in a given ventile (including the unemployed who have zero labor earnings), they confound the effect of monetary policy on labor earnings with those on employment probabilities. Because average earnings $earn_t$ equal the product of the labor earnings of the employed $earn_t^E$ times the employment rate $e_t$, we can decompose log-average earnings as

$$log(earn_t) = log(earn_t^E) + log(e_t) \tag{5}$$

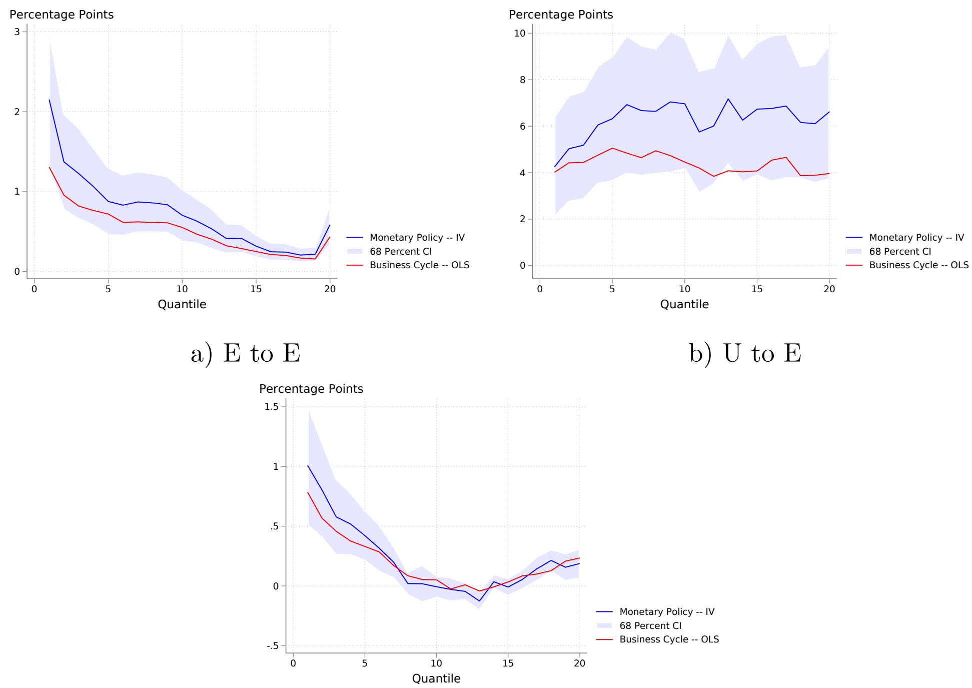
The effect of monetary-policy surprises on average labor earnings is thus the sum of two separate effects on, respectively, the labor earnings of the employed (which we denote the *intensive*-margin effect), and on the employment rate (*extensive*-margin effect).

The right panel of Figure 2 presents point estimates of $\beta_{12}$ for labor earnings of the employed $earn_t^E$, by restricting the estimation sample to those individuals in a given ventile who are employed in periods $t-1$ and $t+12$. The estimates are substantially smaller in magnitude, and less heterogeneous. The point estimates decline along the bottom half of the distribution, but are essentially flat between ventiles 9 and 19, before rising substantially in the top ventile. The difference between the estimates of $\beta_{12}$ on the two samples 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 (as evidenced by a narrowing gap between the gray and blue lines), to about a quarter of the overall effect (but is again more important in the top ventile).

### 4.3 Monetary policy effects on labor market transitions across the income distribution

Figure 2 shows that changes in employment account for more than half of the overall effect of monetary-policy surprises on average labor earnings in a given ventile, and is particularly important at the bottom of the income distribution. In this section, we therefore study how monetary policy affects employment in more detail, by quantifying its effect on the transition probabilities between different labor market states along the income distributions. Similar to the previous section, we estimate $\gamma_{12}^{s1,s2}$, the one-year response of the share of individuals in labor market state $s_1$ who transit to $s_2$ in (2), separately for every ventile of the income distribution, and plot the result in Figure 3.

Figure 3: Regression coefficients $\gamma^q$




a) E to E

b) U to E

c) Switch

**Note:** Panel a) plots the coefficients $\gamma_{12}^{EE}$ (scaled by an expansionary monetary-policy surprise consistent with a one-percent increase in aggregate earnings, blue line) and $\gamma_{12}^{Y,EE}$ (red line), from a version of equations (2) and (4) that take the share of those employed in $t-1$ who transit to employment (E to E) in period $t+12$ as their dependent variable. Panel b) plots the scaled coefficients $\gamma_{12}^{UE}$, and $\gamma_{12}^{Y,UE}$, for the share of unemployed transiting to employment (U to E). Panel c) pots the scaled coefficient $\gamma_{12}^{Switch}$ and $\gamma_{12}^{Y,Switch}$ for the share of the employed who change employment relation. The shaded area indicates 68 percent confidence bands for $\gamma_{12}^{s_1,s_2}$.

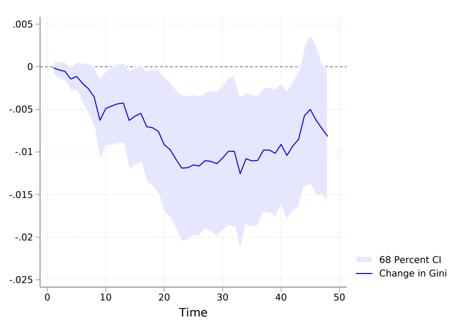
Figure 3 documents strong heterogeneity also in the incidence of monetary-policy surprises on labor market transitions along the income distribution. Panel a) shows the point estimates for $\gamma_{12}^{E,E}$ (scaled by an expansionary monetary-policy surprise consistent with a one-percent increase in aggregate earnings), summarising the effect of a monetary-policy surprise that raises average earnings by one percent on the share of the employed who transit to employment in $t+12$. For the poorest individuals in the sample, in the bottom ventile, the expansionary monetary-policy surprise we focus on decreases the probability of moving to unemployment by on average two percentage points. Moving up the income distribution this effect declines monotonically to about 0.5 percentage points. The top ventile is again affected somewhat more strongly. Interestingly, the reduction in transitions into unemployment is somewhat more pronounced for the expansionary monetary policy shocks than for an unconditional increase in average earnings of similar size as those implied by the shock.

Panel b) of Figure 3 shows the scaled point estimates for $\gamma_{12}^{U,E}$, summarising the effect of an expansionary monetary-policy surprise on the share of the unemployed who transit into employment. This effect is on average more than 5 percentage points. Contrary to the stronger effect on the likelihood of E-to-E transitions, U-to-E transitions respond 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.

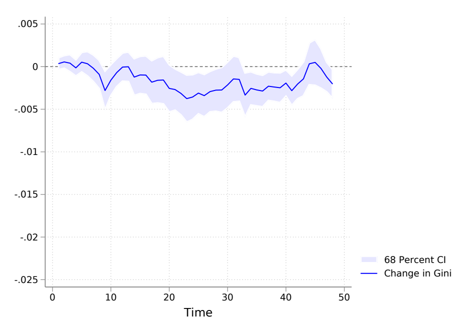
The results in panel a) and b) thus show that the substantially stronger extensive-margin effect of monetary policy on employment shares of the poor is largely accounted for by their more responsive employment-to-employment transitions. Panel c) of Figure 3 further investigates the source of this heterogeneity. 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 affect in the rest of the distribution. A similar pattern holds for the effect on job-switching of unconditional fluctuations in average earnings.

The previous results beg the question how inequality in labor earnings develops in response to a monetary policy shock. Figure 4 plots the response of the Gini coefficient in response to an expansionary monetary policy shock.

Figure 4: Gini coefficient Impulse Response




a) Change in Gini coefficient




b) Change in Gini coefficient, including benefits

**Note:** The panels show the change in the Gini coefficient of labor earnings (including zeros), in response to an expansionary 25 basis point monetary policy surprise, over time. The shaded area indicates 68 percent confidence bands.

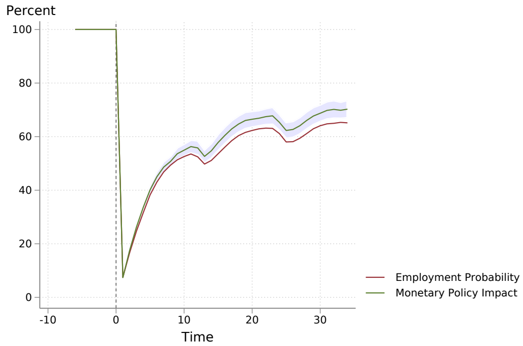
## 4.4 Monetary-policy effects on labor market prospects and earnings after unemployment

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. Because the welfare costs of unemployment are strongly affected by its duration and effect on future earnings, this section investigates the effect of monetary-policy shocks on re-hiring earnings and re-employment probabilities. For this, we focus on individuals who become unemployed in period $t$ and have been employed during the six preceding months. For $k = -6, -5, ..., 36$ we then run the following regression:

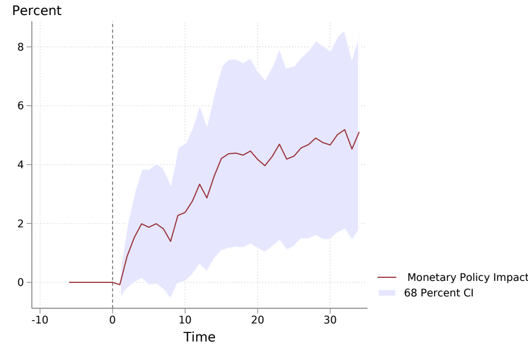
$$y_{t+k} = \alpha_{y,k} + \gamma_{y,k}\Delta i_t + \theta_{y,k}X_t + \epsilon_t$$

where $y \in \{earn, emp\}$ corresponds to monthly individual earnings ($earn_t$) or an indicator variable $emp$ that takes the value 1 when an individual is employed, and 0 otherwise. Again, $\Delta i_t$ represents the interest rate change in period $t$, instrumented using $Z_t$ as before and $X_t$ contains calendar-month dummies and lags of the interest rate change as well as the instrument. In (**??**), $\alpha_{y,k}$ equals the average earnings or employment $k$ months after an unemployment shock in the absence of monetary policy surprises. In turn, $\gamma y, k$ quantifies the impact of monetary policy on these variables. The regression is similar in spirit to that in Davis and Von Wachter (2011), who investigate earnings paths of the unemployed relative to those who remain employed. We, instead, focus on the subsample of those who become unemployed after an employment spell of at least 6 months and report their earnings paths in different monetary policy regimes. Because this substantially reduces the sample size, we report results for terciles, rather than ventiles, of the permanent-income distribution

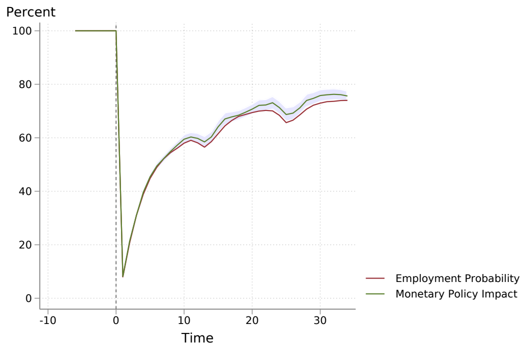
Figure 5: Effect of monetary policy shock on re-employment probabilities



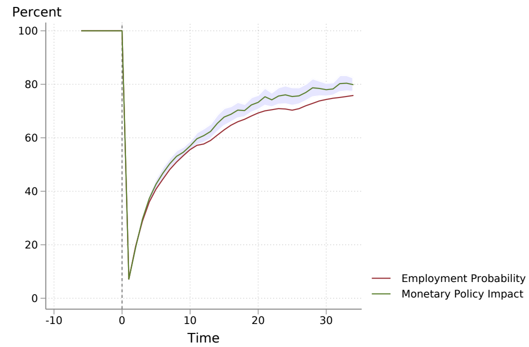

(a) Average employment probability



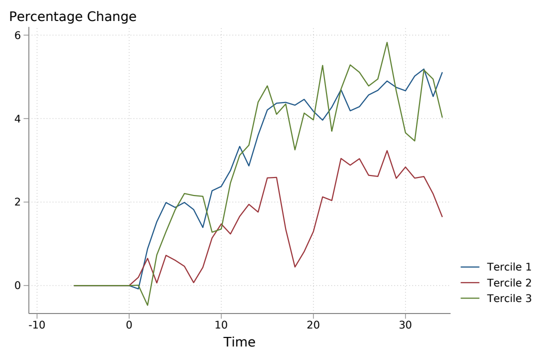

(b) Average employment probability




(c) Average employment probability




(d) Average employment probability

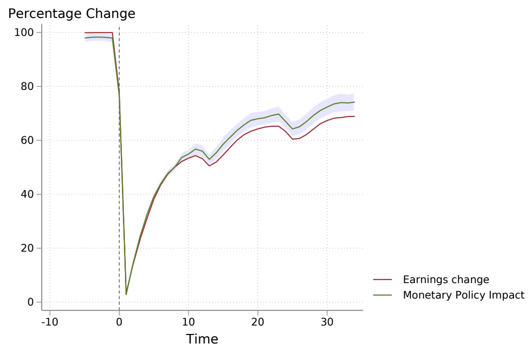



(e) Monetary policy impact on re-employment probabilities

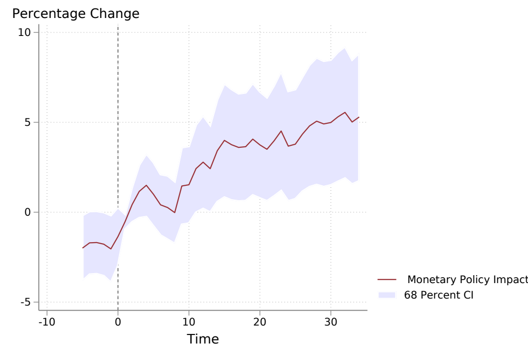
**Note:** The panels show the employment probability of individuals who transition into non-employment in month $t = 0$ with and without a 25 basis point monetary policy surprise (in the blue and red lines, respectively), over time. Panels a),c),d) show results for three subsamples comprising individuals in the lower / middle / upper tercile of the permanent-income distribution, respectively. Panel b) shows the difference between the red and blue line in panel a), corresponding to the effect of a monetary policy surprise on re-employment probabilities of individuals in the lowest tercile. The shaded area indicates 68 percent confidence bands.

Figure 5 shows average re-employment probabilities $\alpha_{emp,k}$ (the red line) and those after an expansionary monetary-policy shock of the same size $\widehat{\Delta i_t}$ considered in the previous section ($\alpha_{emp,k} + \gamma_{emp,k}\widehat{\Delta i_t}$, the blue line). The figure plots the estimates for individuals in the lower (panels a) and b)), middle (c)) and upper tercile (d)) of the income distribution. After one year, average re-employment probabilities are similar, at almost 60 percent, in the three terciles. After that, however, the gradient flattens more for individuals in lower terciles of the income distribution, with a probability of remaining unemployed for longer than two years that is about 5 and 10 percentage points higher in the bottom and middle terciles, respectively, than in the top tercile. An expansionary monetary policy shock increases re-employment probabilities. For the bottom and top terciles, the effect increases to about 4 percentage points after two years and then flattens out, and is slightly smaller in magnitude at 12 months than in the larger sample of all unemployed individuals (in panel b) of Figure 3). The effect is less pronounced in the middle tercile, suggesting that at longer horizons there is a more pronounced U-shape in the effect of monetary policy on labor market transitions than at the 12-month horizon considered in Figure 3.

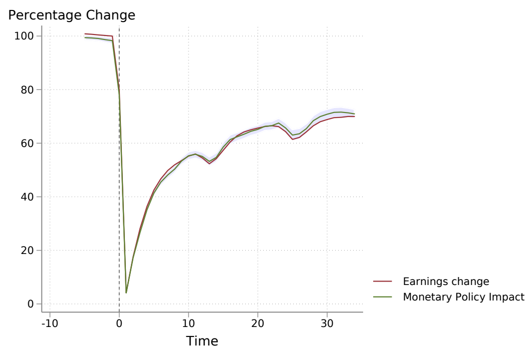
Figure 6: Effect of monetary policy on average earnings after unemployment



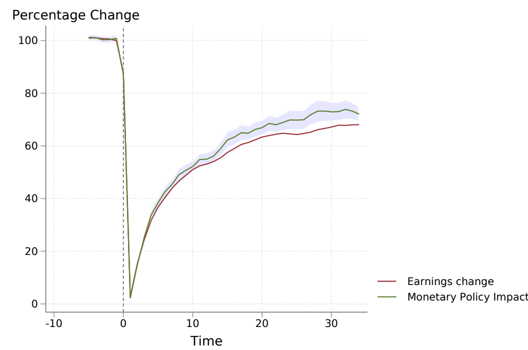

(a) Earnings level following unemployment




(b) Earnings level following unemployment




(c) Earnings level following unemployment

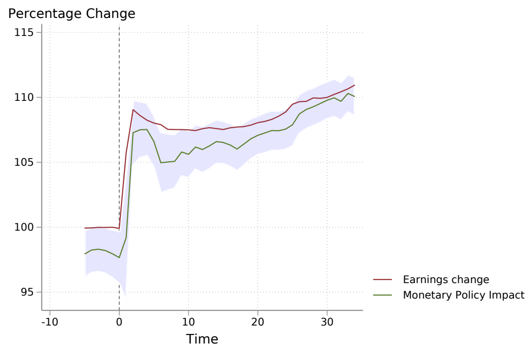



(d) Earnings level following unemployment

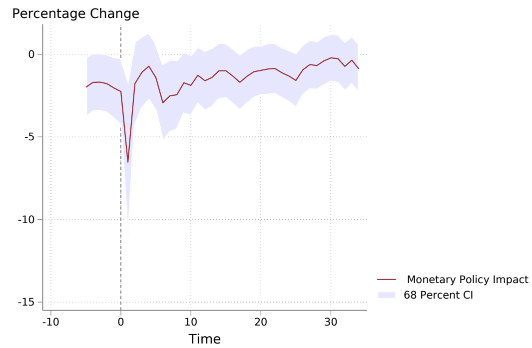
**Note:** The panels show the average earnings of individuals who transition into unemployment in month 0 with and without a 25 basis point monetary policy surprise (in the blue and red lines, respectively), over time. Panels a),c),d) show results for three subsamples comprising individuals in the lower / middle / upper tercile of the permanent-income distribution, respectively. Panel b) shows the difference between the red and blue line in panel a), corresponding to the effect of a monetary policy surprise on earnings of individuals in the lowest tercile. The shaded area indicates 68 percent confidence bands.

Figure 6 shows that, unsurprisingly, average earnings after an unemployment event follow a path very similar to that of re-employment probabilities over time, and across the income distribution. Figure 7 shows the effect of monetary-policy surprises on the average earnings of those who become unemployed in period $t$ but have found a new employment relationship in $t + k$ (the earnings of the re-employed). In the upper and middle tercile, this measure is downward sloping, corresponding to a negative effect of longer unemployment spells on re-employment earnings. This earnings loss is most pronounced in the upper tercile, with about 7 percent on average after two years. Surprisingly perhaps, in the bottom tercile earnings of those who find a new job quickly are higher than those before the unemployment event. This reflects a strongly positive effect of job changes on incomes at the bottom of the income distribution. To understand the effects of monetary policy on re-employment earnings,

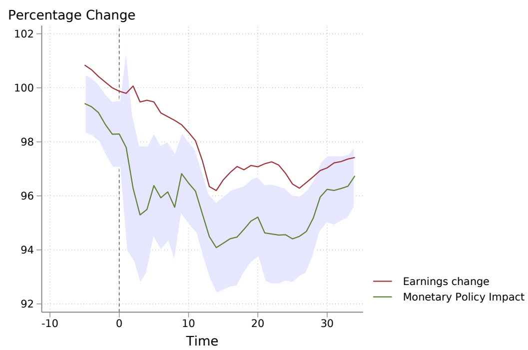
Figure 7: Effect of monetary policy on re-employment earnings of the re-employed



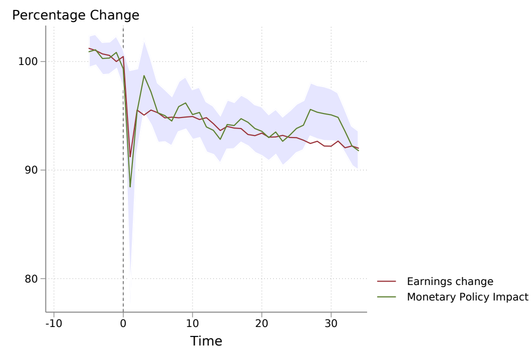

(a) Earnings level following unemployment




(b) Earnings level following unemployment




(c) Earnings level following unemployment




(d) Earnings level following unemployment

**Note:** The panels show the average earnings of individuals who transition into unemployment in month 0 and are employed again in period $k$, with and without a 25 basis point monetary policy surprise (in the blue and red lines, respectively), over time. Panels a),c),d) show results for three subsamples comprising individuals in the lower / middle / upper tercile of the permanent-income distribution, respectively. Panel b) shows the difference between the red and blue line in panel a), corresponding to the effect of a monetary policy surprise on re-employment earnings of individuals in the lowest tercile. The shaded area indicates 68 percent confidence bands.

note that they have both an earnings effect (through earnings changes for similar individuals and unemployment duration) and a composition effect (whereby higher re-employment probabilities change the pool of the unemployed). The combined effect is slightly negative, but small.

# 5 Heterogeneous incidence and the propagation of monetary policy

The empirical evidence suggests that monetary policy interventions have strongly heterogeneous effects on the earnings and employment prospects along the income distribution in Germany. But does this observed heterogeneity change the transmission mechanism of monetary policy to *aggregate* demand and inflation? Indeed, a recent literature has pointed out that heterogeneity in incomes and employment risk may amplify fluctuations in aggregate demand whenever incomes of individuals with high marginal propensity to consume are more cyclical Auclert (2019), or when increased unemployment risk boosts precautionary savings of imperfectly insured workers in recessions Werning (2015). In this section, we thus quantify how the heterogeneous cyclicality of incomes and labor market transitions changes the transmission of monetary policy shocks to output and inflation. For this, we study the general equilibrium of a workhorse model for policy analysis in the New Keynesian tradition, where endogenous unemployment risk feeds back to demand via precautionary savings, and where workers differ in their exposure to monetary policy shocks through heterogenous effects on their earnings and employment prospects. The model environment is an extension of that in Ravn and Sterk (2017) to two types of workers and endogenous job separations. [Relegate much of the following to appendix?]

## 5.1 Households and firms

There are two types of infinitely-lived workers of equal mass denoted $L$ and $H$, indexed by $i \in [0, 0.5)$ and $i \in [0.5, 1]$, respectively. Their type associates them with one of two separate labor-markets, where they receive wage income $W_t^k$ if employed and $\vartheta W_t^k$ if unemployed (we think of $\vartheta$, for simplicity, as a replacement rate derived from home production). Workers have identical CRRA preferences with discount factor $\beta$ and risk aversion $\sigma$ and differ only in their labor market characteristics (productivity, wage, separation and job-finding probability). Risk-neutral infinitely-lived capitalists indexed by $i \in (1, 1+\text{pop}_c]$ and with the same discount factor $\beta$ own all firms.

Production has three layers: A continuum of intermediate-good firms hire labor in two separate, type-specific labor markets subject to search and matching frictions. Every match produces a type-specific quantity $a_t^k$ of a homogeneous good sold in a perfectly competitive market at price $P_t^X$. Total production of intermediate goods is

$$X_t = \sum m^k a_t^k (1 - u_t^k). \tag{6}$$

where $m^k$ is the mass of type $k$ workers. Wholesale firms buy these intermediate goods as inputs to produce differentiated goods with a simple linear production technology, sold in a market with monopolistic competition at prices subject to a Rotemberg adjustment cost. Final-good firms buy different wholesale and use a standard CES aggregator to bundle them in a final good that is sold in a perfectly competitive market at price $P_t$.
The assumptions on the production sector imply a standard Rotemberg Phillips curve

$$1 - \xi + \xi \cdot P_t^X = \xi(\Pi_t - 1)\Pi_t - \beta\xi\mathbb{E}_t\left[(\Pi_{t+1} - \Pi_{ss})\Pi_{t+1}\frac{Y_{t+1}}{Y_t}\right] \tag{7}$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$ is the gross inflation rate, with total output of final goods given by

$$Y_t = X_t. \tag{8}$$

## 5.2 Intermediate goods production and labor-market dynamics

After type-specific productivity $a_t^k$, $k \in L, H$, is revealed, intermediate goods firms that were matched in $t-1$ draw idiosyncratic continuation cost shocks from a labor-type-specific distribution and decide whether to continue or exit. We denote the resulting endogenous, time-varying separation rate $\delta_t$ and make assumptions on the distribution of costs that imply a constant elasticity $\epsilon_j^k$ of job separations to the value of a job, defined as

$$J_t^k \quad = \quad P_t^X A_t a_t^k - W_t^k + (1 - \delta_{t+1}^k)\beta\mathbb{E}_t(J_{t+1}^k - \mu_{t+1}^k) \tag{9}$$

where $W_t^k$ is the real wage of a type k worker and $\mu_t^k$ is the average separation cost paid. Unemployment before the matching stage is thus described by

$$1 - \underline{u}_t^k \quad = \quad (1 - \delta_t^k)(1 - u_{t-1}^k),$$

where $u_t^k$ is the stock of unemployed workers at the beginning of the period.
Non-matched firms then decide whether to post vacancies at a flow cost $\kappa$, identical for both labor markets. Because of free entry to vacancy posting the value of a vacancy equals 0 in both labor markets in all periods ($V_t^{v,k} = 0$). Stochastic matching then takes place between unemployed workers and vacancies in the two labor-markets for type L and H workers separately. The matching technology is Cobb-Douglas, with job-filling rate $q_t^k$ and job-finding

rate $f_t^k$. The post-matching labor-market stocks are

$$u_t^k \;=\; (1 - f_t^k)\underline{u}_t^k, \tag{10}$$

We assume that wages are rigid, following

$$W_t^k = (\overline{W}_t^k)^{(1-\eta)}(W_t^k)^{\eta}, \tag{11}$$

where $\overline{W}_t^k$ denotes the steady state wage of type $k$ workers

## 5.3 Consumption and savings decisions

After production has taken place wages and dividends are paid to workers and capitalists, respectively, who then make their consumption- and saving decisions. Capitalists can buy and sell shares in an equity fund that owns all firms, but do not participate in the labor market. Workers can save in a zero-coupon one-period nominal bond, in zero net supply, which can be purchased at the price $1/(1+i_t)$ where $i_t$ is the nominal interest rate, and face a no-borrowing constraint.

Because of zero net supply and no borrowing, the equilibrium interest rate clears the market only if all households decide not to save, implying that borrowing constraints bind for all households apart from the type with the highest incentive to save.[13] The model therefore admits analytical aggregation. Specifically, as in **?**, under the assumption that aggregate shocks are small, the precautionary motive to save against idiosyncratic unemployment risk always gives the employed worker with the currently highest unemployment risk the strongest motive to save, and in equilibrium, the interest rate must only be consistent with that type's Euler equation for consumption. Together with the no-borrowing constraint and the zero net supply of assets, this yields the following standard asset-market clearing condition,

$$(W_t^j)^{-\sigma} = \beta \mathbb{E}_t\left[\frac{1+i_t}{\Pi_{t+1}}\left\{(1-\mathrm{URISK}_t^k)(W_{t+1}^k)^{-\sigma} + \mathrm{URISK}_t^k \vartheta^{-\sigma}\right\}\right]. \tag{12}$$

where $\mathrm{URISK}_t^k = \delta_{t+1}^k(1 - f_{t+1}^k)$ is the probability that an employed household is unemployed in the next period.

[13]Formally, any real interest rate low enough such that all four Euler equations are satisfied with weak inequality is consistent with the zero-borrowing limit. The natural interpretation is however to let liquidity approach zero, as in **?**, then the real interest rate is such that one of the Euler equations holds with equality.

## 5.4 Government

A government sets monetary policy according to a particularly simple Taylor rule that is helpful for explaining the model interactions.

$$1 + i_t = (1 + i_{ss})\Pi_t^{\phi_\pi - 1} E_t \Pi_{t+1}. \tag{13}$$

The interest rate reacts to both expected and current inflation, such that real interest rate reacts to current inflation with elasticity $\phi_\pi - 1$.

## 5.5 Parameter choice

We set the discount factor $\beta$ to 0.997 and a price elasticity $\epsilon_p$ of 6, all standard values. To illustrate how the precautionary-savings channel depends on preferences, we present results for two values of risk aversion $\sigma$ equal to 2.5 and 5, respectively. Following **?**, we set the earnings replacement rate for the non-employed to 90 %. Table 2 summarises the externally chosen parameter values.

We choose the remaining parameters such that the model matches key features in our data. For this, we identify the two types of workers with individuals below and above the median of the earnings distribution. As for the quantiles in Section 4, we calculate group-specific steady state earnings, unemployment rates and transition probabilities from employment to unemployment, and the cyclicality of earnings growth and transition probabilities in response to monetary-policy shocks. Since our model abstracts from sources of persistence that are likely important for the medium-run dynamics,[14] we choose model parameters to match short- and long-run features of the data. In particular, we target,the steady state unemployment and transition rates, and the effects of monetary-policy shocks on one-period transition probabilities and earnings growth rates. Table **??** summarises the parameter values and Table **??** the target moments. The model matches the target moments well, with the exception of the 12-month transition to unemployment of the high type: although separations that are inelastic, a strong response of job-finding makes the transitions slightly more cyclical than in the data. The moments predicted by the model with higher risk aversion ($\sigma = 5$) are very similar.

Externally calibrated Parameters

[14]See Broer et al. (2021), for evidence on the relative persistence of different labor market transition rates, and a a model with sluggish vacancy creation that matches these.

Table 2: Externally calibrated parameters

| Name | Parameter | Value |
|---|---|---|
| Discount Factor | $\beta$ | $0.96^{1/12}$ |
| Risk Aversion | $\sigma$ | 2.5 (5) |
| Replacement rate | $\vartheta$ | 0.9 |
| Price elasticity | $\epsilon_p$ | 6.0 |
| Rotemberg parameter | $\phi$ | 600.0 |
| Vacancy cost | $\kappa$ | 0.58 $a^i$,$i = L, H$ |
| Taylor rule parameter | $\phi_\pi$ | 1.5 |
| Matching function parameter | $\alpha$ | 0.7 |

Table 3: Endogenously calibrated parameters

| Name | Type | Parameter | Value |
|---|---|---|---|
| Wage flexibility low type | | $\eta$ | - 0.0335 |
| Wage flexibility high type | | $\eta$ | - 0.012 |
| Separation Elasticity | L | $\epsilon_j^L$ | .07 |
| | H | $\epsilon_j^H$ | 0.00058 |
| Steady state separations | L | $\delta_{ss}^L$ | 0.0057 |
| | H | $\delta_{ss}^H$ | 0.0035 |
| Productivity | L | $a^L$ | 0.72 |
| | H | $a^H$ | 1.28 |

Table 4: Target Moments

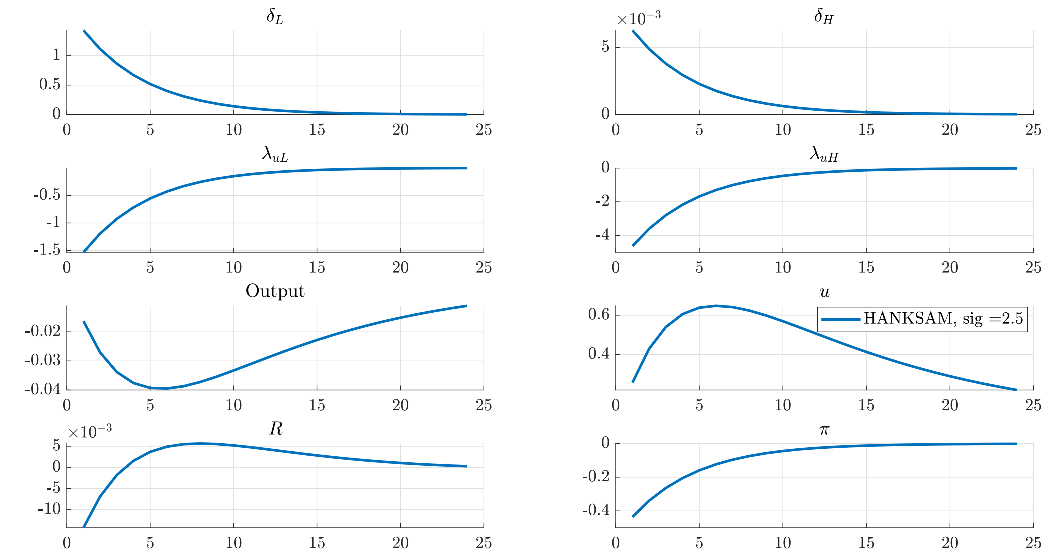
| Name | Type | Data | Model ($sigma = 2.5$) |
|---|---|---|---|
| Relative steady state earnings of $H$ type | | 2.0 | 2.0 |
| Steady state unemployment | L | 0.11 | 0.10 |
| | H | 0.022 | 0.02 |
| 12m E to U – SS | L | 0.0482 | 0.0488 |
| | H | 0.0177 | 0.0171 |
| 12m E to U – MP | L | 0.092 | 0.090 |
| | H | 0.034 | 0.039 |
| 12m Earnings Beta | L | -0.0488 | -0.048 |
| | 0.043 | 0.044 H | -0.0431 |
| -0.0374 | | | |

## 5.6 Model Results

### 5.6.1 Impulse responses in the benchmark model

Figure 8 reports the impulse responses to a contractionary monetary-policy shock equal to 100bp, the same as in the empirical analysis of Figure ??, when $\sigma$ equals 2.5. The separation probability of low types rises strongly in response to the shock, while that of high types is (essentially) constant. Job-finding of high types, in contrast, responds stronger than that of low types (in percentage terms), which, although not targeted, is qualitatively in line with data.

Figure 8: Model output



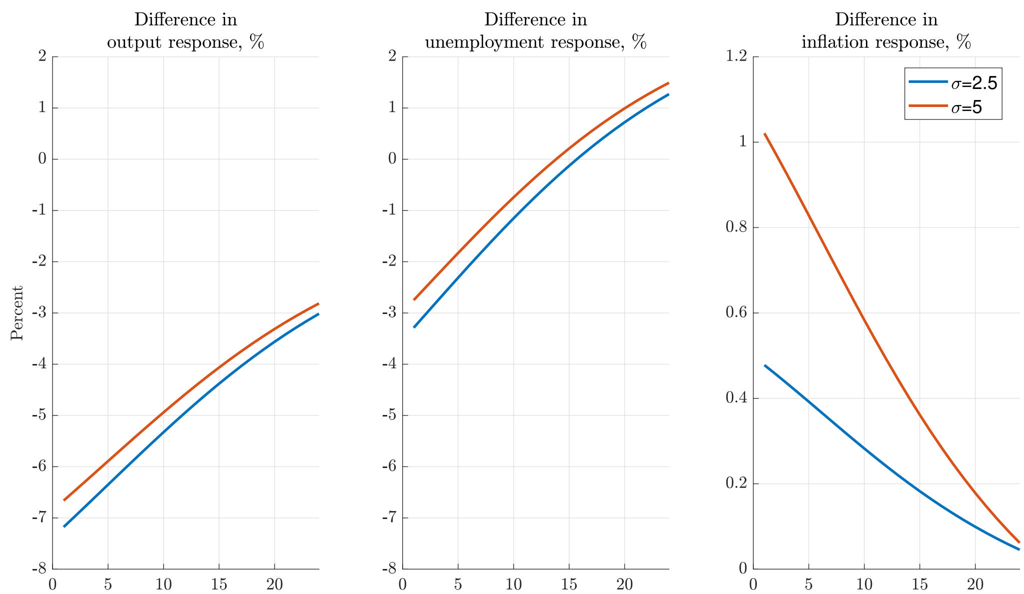

**Note:** This Figure shows the responses to a one-time monetary policy in the benchmark environment.

To quantify the importance of the heterogeneous incidence for aggregate consumption demand, we compare the cumulative responses of output, unempoyment and inflation in the benchmark two-type model to those in two alternatives.

### 5.6.2 Heterogeneous incidence dampens the supply response [New. If interesting, perhaps should do at benchmark prices]

We first highlight how the weaker response of the labor market for highly productive workers in the benchmark environment dampens the aggregate output response to monetary-policy shocks that is dominated by high-type employment. For this we compare the benchmark model with an alternative that differs from the benchmark only in that the response of separation risk is now the same for low and high types. For this we set the separation elasticity $\epsilon_j^L$ to the (employment-weighted) average of the two benchmark parameters, equal to . Figure 9 shows how the weaker incidence of shocks on high-productivity workers in the benchmark model strongly dampens the responses of output relative to the one-type model where separations of high-productivity workers respond more strongly. The response of unemployment, in contrast, is only mildly larger in the benchmark model, with the difference turning positive after about a year.

Figure 9: Model output




**Note:** This Figure shows the percentage difference between the cumulative impulse responses in the benchmark model and in the comparison one-type model with an identical separation elasticity (as a percentage of the latter), with a positive difference implying a stronger response from the 2-Type model.

### 5.6.3 Heterogeneous incidence amplifies the demand response [As before]

While the weaker response of employment for high-productivity workers dampens output effects of monetary policy, we show in this section how heterogeneity in labor market risk per se amplifies the aggregate demand response through more cyclical precautionary savings. For this, we compare the benchmark economy outlined above to a standard environment with a representative employed worker and a representative unemployed worker, whose consumption in all states of nature equals the average of two types in the benchmark environment. To isolate the effects of heterogeneous labor market risk on demand, we keep the underlying production technology, with two types of labor and two types of firms, unchanged, but eliminate any heterogeneity beyond that of labor market status by pooling consumption of the employed and unemployed.[15] Thus, by construction, any difference in responses

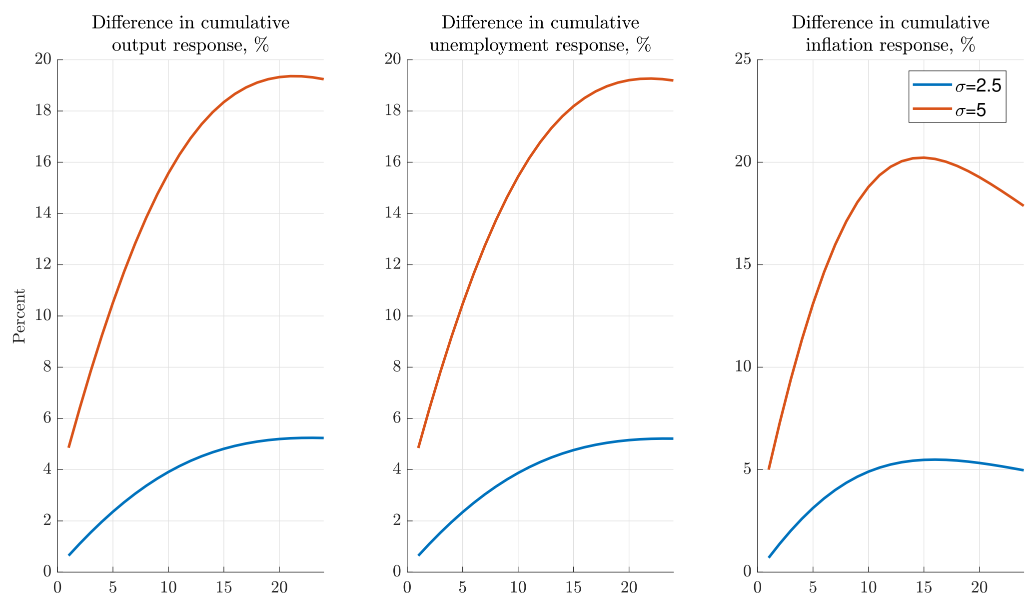
[15]This corresponds to an environment where workers are ex-ante uncertain about the type they are and can completely insure their consumption against that source of risk.

between the benchmark two-type model and the one-type comparison captures the effect of consumption-heterogeneity on the transmission of monetary policy shocks.

Both unemployment and inflation respond substantially more in the two type model. So the heterogeneous consumption risk implied by heterogeneous exposure to the shock amplifies its effect. Figure 8 summarises this amplification by showing the percentage difference between the cumulative impulse responses in the benchmark model and those in the comparison one-type model (as a percentage of the latter), with a positive difference implying a stronger response from the 2-Type model. After 18 months, the cumulative response of average unemployment is about 20 percent higher in the benchmark model (5 percent with lower risk aversion equal to $\sigma = 5$). The fall in inflation response is similarly amplifiied. Output intially responds more in the one-type model, as the unemployment response of high types is stronger there.

What explains this substantial boost of the monetary-policy effects on aggregate output and inflation? Note that the earnings and labor market risk of $L$ types is higher, and more volatile than that of $H$ types.[16] This implies more volatile aggregate consumption demand than in the one-type model.

Figure 10: Model output




**Note:** This Figure shows the percentage difference between the cumulative impulse responses in the benchmark model and those in the comparison one-type model (as a percentage of the latter), with a positive difference implying a stronger response from the 2-Type model.

[16]Their higher steady state separation rates imply a higher average value of $\text{URISK}_t^k$ for $L$ types in (12).

# 6 Conclusion

[TO BE ADDED]

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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.

## A.1 Sample selection

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[17]) and the unemployed, defined as individuals who received unemployment benefits at the beginning of their current non-employment spell. We restrict our sample to workers who have at least one earnings observation in the five years prior to period $t$, in order to calculate our permanent-income measure.

When estimating earnings growth rates, we exclude observations that do not contain genuine information about earnings growth, i.e. when an individual's earnings are top coded both at the beginning *and* the end of a period over which earnings growth is calculated (and where any change in earnings is therefore entirely due to the imputation procedure described below). We do not exclude individuals who, e.g., have a non-censured earnings observation in period $t-1$, but are censored (and thus have imputed earnings) in period $t+12$.

## A.2 Imputation

We impute data that is likely due to spell errors following Drews et al. (2007) and impute education where data are missing or inconsistent following Fitzenberger et al. (2005). Further, we impute top-coded earnings observations using the procedure proposed by Dauth and Eppelsheimer (2020), which in turn relies on Dustmann et al. (2009) and Card et al. (2013). However, we modify their approach in three ways: (i) because we manually censor the data from above at the 94th percentile , (ii) when imputing the censored wages, we only include non-marginally employed individuals without special characteristics in the tobit regression, and (iii) in the second step of the imputation procedure, we categorize individuals by spells, as opposed to firms, since we do not have access to the firm-worker matched dataset. In what follows, we explain each step in more detail.

In our dataset, the assessment ceiling for social security contributions changes slightly each year, leading to an approximately constant percentage of censored wages. However, in 2003, the limit rises more substantially than in other years, reducing the number of censored observations considerably (from close to 5 percent to closer to 3 percent). At the same

[17]Marginal part-time workers are defined as those individuals who earn an income below the assessment floor for social security contributions.

time an unusual share of marginally attached workers are newly registered as employed in April of the same year, as opposed to January. Both of these occurances lead to implausible aggregate earnings movements after the imputation. To combat this, we manually censor all observations above the 94th percentile (close to or above the assessment ceiling in most years). Further, to avoid changes in the imputation procedure originating from the inclusion of marginally employed workers (who are likely a bad indicator for censored earnings), we exclude them from the imputation procedure.

The imputation procedure by Dauth and Eppelsheimer (2020) proceeds in two steps, first imputing censored earnings based on observable characteristics and then including imputed, firm-specific leave-one-out means into said regression in a second step. Unfortunately, we do not have access to firm-worker matched data, and hence we exchange the firm-specific means with spell-specific means. The imputations from the first- and second step are close to identical in our setting.

# B Additional Results

## B.1 Aggregate responses to monetary policy surprises

Before moving to individual incomes, we investigate the effect of monetary policy shocks on the aggregate economy. We run the following local projection regression following Jordà (2005)

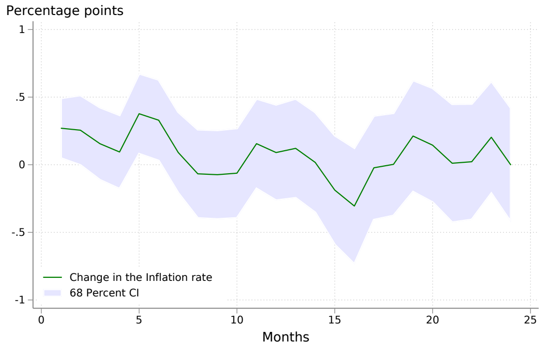
$$x_{t+h} - x_{t-1} = \alpha + \beta_h \Delta i_t + \gamma_h X_{t-1} + \varepsilon_{t,h} \tag{14}$$

where $\Delta i_t$ captures the change in the ECB's policy rate, $x$ represents (i) the monthly inflation rate as measured by the logarithm of German HICP, (ii) the logarithm of industrial production or (iii) the German unemployment rate. The vector $X_{t-1}$ represents a set of control variables consisting of one lag of the instrument $Z_t$, $\Delta i_t$ and of $x$; lastly, it contains calendar month dummies.

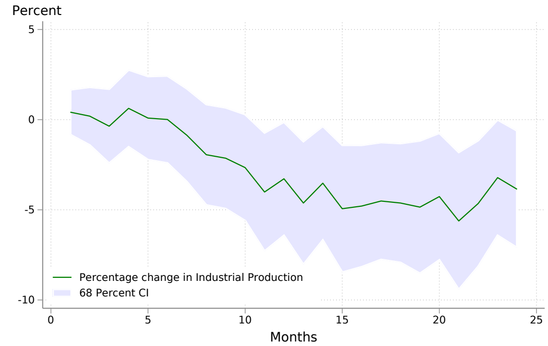
Figure 11 shows the impulse responses to a 25 basis point shock to the interest rate, estimated using Equation (14). The horizontal axis measures time after the monetary policy surprise in months, the vertical axis measures the percentage point change in the aggregate in question. The unemployment rate (bottom panel) increases and industrial production (top right panel) declines in response to the surprise increase in the policy rate. Both respond with a lag of about 6 to 8 months, and then follow a hump-shaped pattern. The responses are, however, rather imprecisely estimated. This is particularly true for the response of inflation (top left panel).

For consistency with the previous literature, we report impulse responses for a 25 basis point

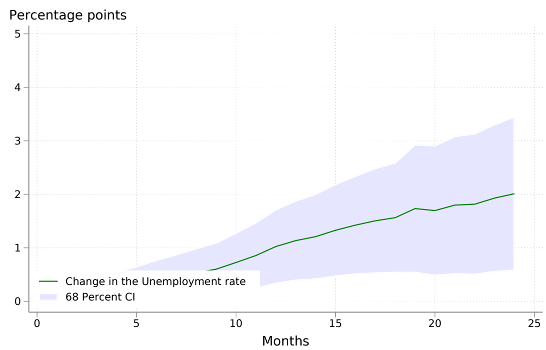
Figure 11: Aggregate responses to monetary policy surprises




(a) Impulse response of the inflation rate




(b) Impulse response of Industrial Production




(c) Impulse response of the unemployment rate

**Note:** The Figure shows the impulse responses of aggregate variables to a 100 bp surprise increase in the the policy interest rate, estimated using the Local Projection outlined in Equation (14). 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 industrial production, calculated as the log difference, and the *Bottom Panel* shows the change in the unemployment rate. The sample period is from 2000 until 2014. The shaded areas indicate 68 percent confidence intervals.

shock to the nominal interest rate. The magnitudes of the responses are large, especially when compared to what is usually found in the literature when responses are estimated using standard VARs, i.e. without the use of external instruments (e.g., Christiano et al., 1999). This difference in magnitudes also arises when comparing single equation approaches to externally identified VARs, i.e. SVAR-IV (Coibion et al., 2012; Stock and Watson, 2018). It is important to note, however, that the standard deviation of our shock series is 2 basis points. Because the coefficient in our first stage regression takes a value of 1.4, this implies that a large monthly surprises in our sample affects the nominal interest rate by 3 basis points. Consequently, a 25 basis point surprise should be, in reference to our sample, considered to be a very large outlier, leading to very strong movements in the outcome variables.