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. We compare this heterogeneous incidence of monetary-policy shocks to that of average business-cycle movements in our sample.

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 Δi_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

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

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 β_h captures the effect on earnings growth between periods t and $t+h$ of a change in interest rates Δi_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 Δi_t and Z_t. ϵ_{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:

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

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 Δi_t and Z_t.

We compare the dynamic effect of monetary policy shocks captured by β_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

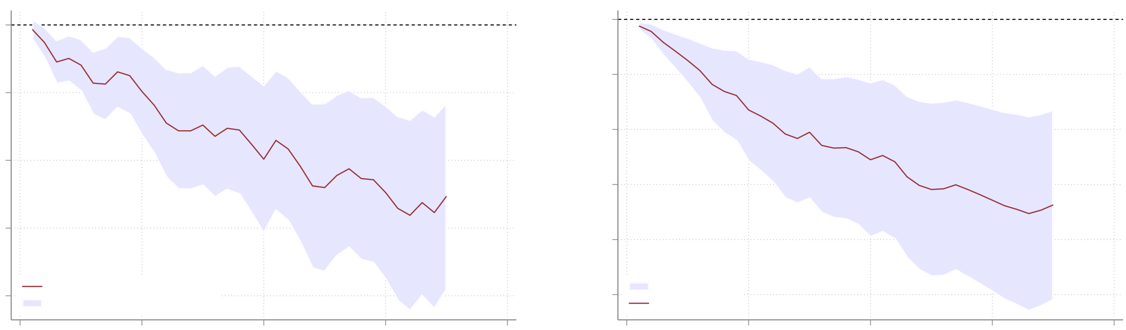
An appendix documents that the monetary-policy surprises we identify affect aggregate variables in line with what has been documented in previous studies (Almgren et al., 2019; Georgiadis, 2015). In particular, a contractionary monetary-policy surprise has little effect on inflation in Germany, but implies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



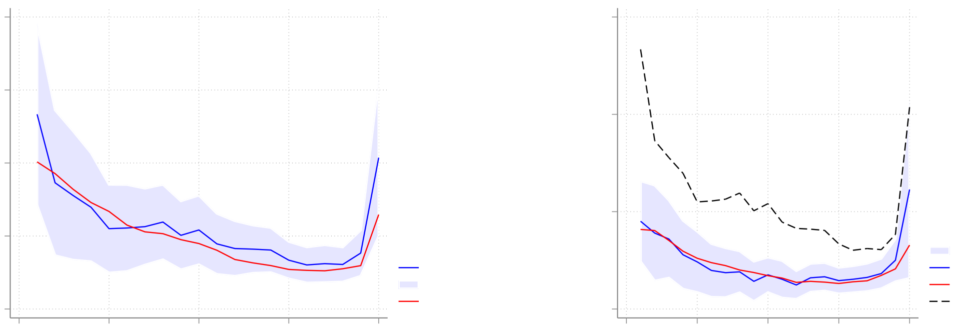
a) Regression coefficients β_h for the full sample   b) Regression coefficients γ_h for the full sample

Note: Panel a) plots the coefficient β_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 β_{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 β_{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 β_{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 β_{12} for all individuals in a ventile (gray dashed line) to β_{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 β_{12} .

The point estimates of β_{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 β_{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

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

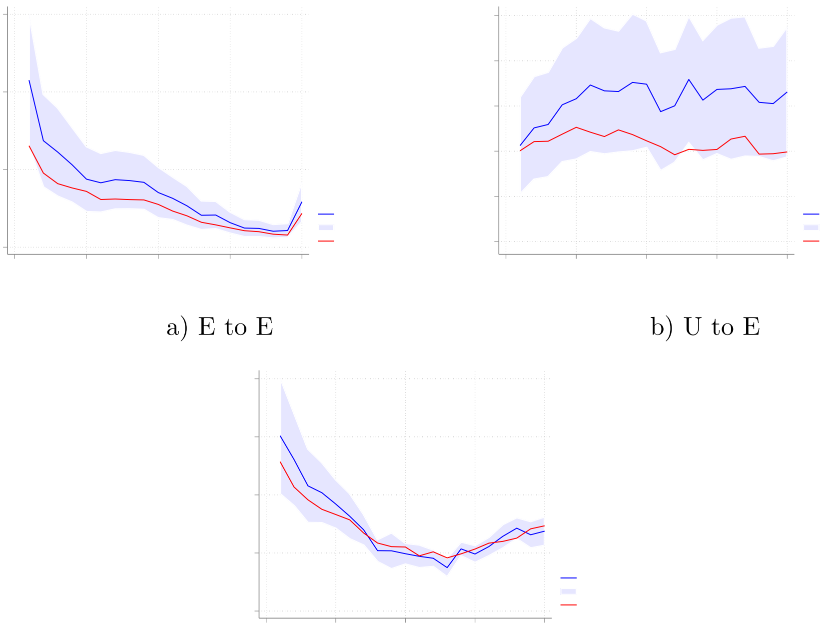
The effect of monetary-policy surprises on average labor earnings is thus the sum of two separate effects on, respectively, the labor earnings of the employed (which we denote the *intensive*-margin effect), and on the employment rate (*extensive*-margin effect).

The right panel of Figure 2 presents point estimates of β_{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 β_{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 γ^q



a) E to E

b) U to E

c) Switch

Note: Panel a) plots the coefficients γ_{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 γ_{12}^{UE}, and $\gamma_{12}^{Y,UE}$, for the share of unemployed transiting to employment (U to E). Panel c) pots the scaled coefficient γ_{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 $\gamma_{12}^{s_1,s_2}$.

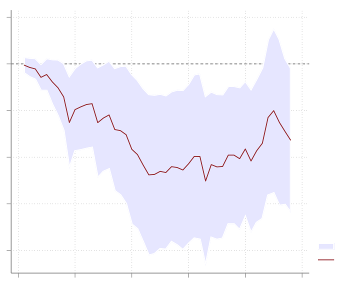
Figure 3 documents strong heterogeneity also in the incidence of monetary-policy surprises on labor market transitions along the income distribution. Panel a) shows the point estimates for $\gamma_{12}^{E,E}$ (scaled by an expansionary monetary-policy surprise consistent with a one-percent increase in 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.

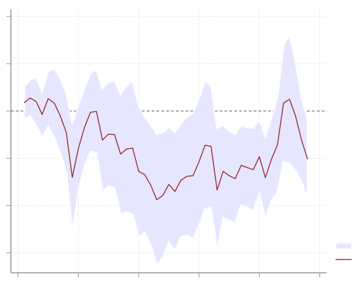
The results in panel a) and b) thus show that the substantially stronger extensive-margin effect of monetary policy on employment shares of the poor is largely accounted for by their more responsive employment-to-employment transitions. Panel c) of Figure 3 further investigates the source of this heterogeneity. 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 a contractionary 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 a 25 basis point monetary policy surprise, over time. The shaded area indicates 68 percent confidence bands.

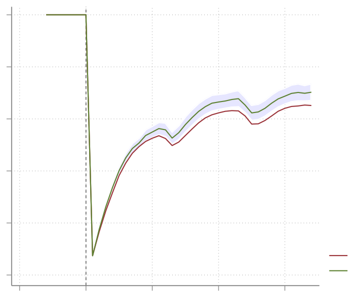
4.4 Monetary-policy effects on labor market prospects and earnings after unemployment

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:

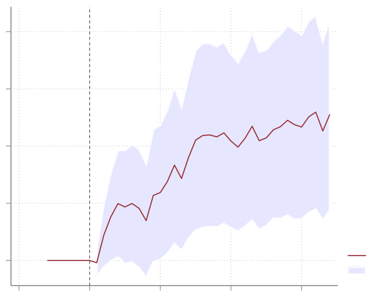
$$y_{t+k} = \alpha_{y,k} + \gamma_{y,k}\Delta i_t + \theta_{y,k}X_t + \epsilon_t$$

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, Δi_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

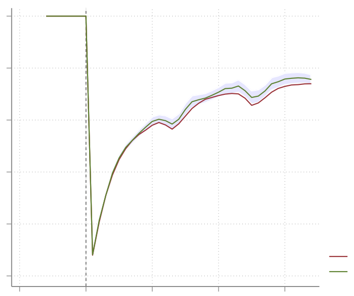
Figure 5: Effect of monetary policy shock on re-employment probabilities



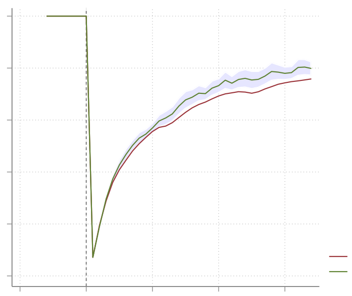
(a) Average employment probability



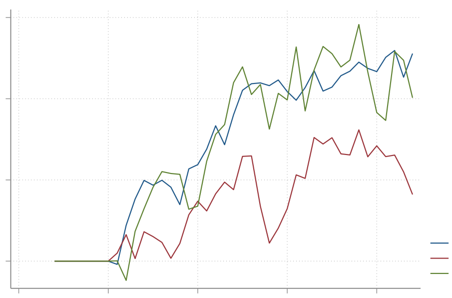
(b) Average employment probability



(c) Average employment probability



(d) Average employment probability

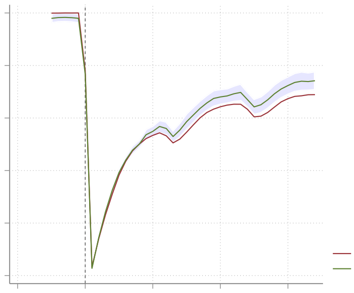


(e) Monetary policy impact on re-employment probabilities

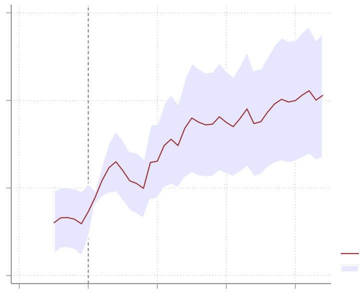
Note: The panels show the employment probability of individuals who transition into non-employment in month $t = 0$ with and without a 25 basis point monetary policy surprise (in the blue and red lines, respectively), over time. Panels a),c),d) show results for three subsamples comprising individuals 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.

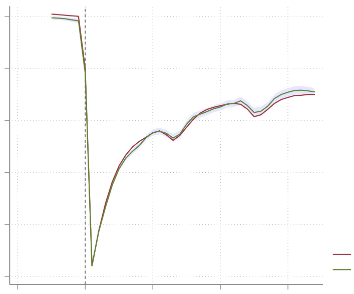
Figure 6: Effect of monetary policy on average earnings after unemployment



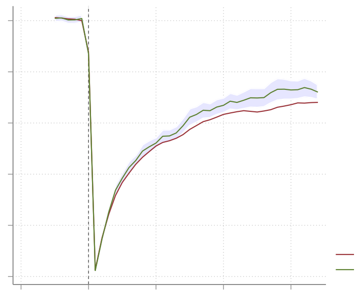
(a) Earnings level following unemployment



(b) Earnings level following unemployment



(c) Earnings level following unemployment

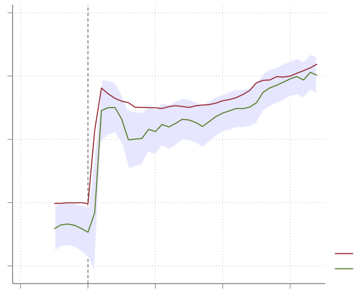


(d) Earnings level following unemployment

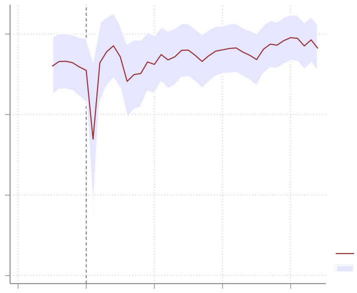
Note: The panels show the average earnings of individuals who transition into unemployment in month 0 with and without a 25 basis point monetary policy surprise (in the blue and red lines, respectively), over time. Panels a),c),d) show results for three subsamples comprising individuals in the lower / 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,

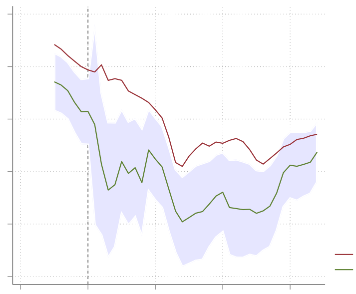
Figure 7: Effect of monetary policy on re-employment earnings of the re-employed



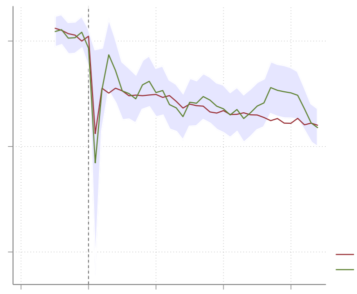
(a) Earnings level following unemployment



(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 Conclusion

Using administrative data from Germany, we show that monetary policy has heterogeneous effects along the earnings distribution, both on labor market transitions rates and on earnings. We use an LPIV approach, instrumenting ECB interest rate changes between 2000 and 2012

with high-frequency changes in Overnight Indexed Swap rates in a narrow window around the announcements, to establish the causal effect of monetary policy surprises on labor market outcomes.
Along the recent earnings distribution, all quantiles experience significant earnings rises within the 12 months following an accommodating monetary policy surprise. However, the bottom sees earnings rise by twice as much, in terms of percentage changes, as the top. By separately estimating the effects on the continuously employed, we show that a large contributor to the heterogeneity are heterogeneous extensive margin transitions. The Gini-coefficient falls in response to accomodative monetary policy surprises.
Investigating employment prospects after non-employment spells, we find that poor individuals who transitions to non-employment after a surprising interest rate cut see their earnings catch up with the pre-unemployment earnings faster than those separated during times without a monetary policy event. Since re-employment earnings don't react significantly to monetary policy surprises, we conclude that the effect is driven by changes in re-employment probabilities. The effect is less pronounced in the middle and upper tercile of the recent earnings distribution.
The documented heterogeneity in the incidence of monetary policy on earnings grwoth is potentially important for understanding the transmission and welfare effects of monetary policy. We view this as a fruitful avenue for future research.

References

Acharya, S., E. Challe, and K. Dogra (2020). Optimal monetary policy according to hank.

Almgren, M., J. E. Gallegos, J. Kramer, and R. Lima (2019). Monetary policy and liquidity constraints: Evidence from the euro area. *Available at SSRN 3422687*.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review 109*(6), 2333–67.

Bilbiie, F. O. (2020). The new keynesian cross. *Journal of Monetary Economics 114*, 90–108.

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly journal of economics 128*(3), 967–1015.

Challe, E. (2020). Uninsured unemployment risk and optimal monetary policy in a zero-liquidity economy. *American Economic Journal: Macroeconomics 12*(2), 241–83.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics 1*, 65–148.

Coibion, O., Y. Gorodnichenko, L. Kueng, and J. Silvia (2012). Innocent bystanders? monetary policy and inequality in the us. Technical report, National Bureau of Economic Research.

Dauth, W. and J. Eppelsheimer (2020). Preparing the sample of integrated labour market biographies (siab) for scientific analysis: a guide. *Journal for Labour Market Research 54*(1), 1–14.

Davis, S. J. and T. Von Wachter (2011). Recessions and the costs of job loss. *Brookings papers on economic activity 2011*(2), 1.

De Nardi, M., G. Fella, M. Knoef, G. Paz-Pardo, and R. Van Ooijen (2019). Family and government insurance: Wage, earnings, and income risks in the netherlands and the us. *Journal of Public Economics 193*, 104327.

Drews, N., D. Groll, and P. Jacobebbinghaus (2007). Programmierbeispiele zur aufbereitung von fdz personendaten in stata.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009). Revisiting the german wage structure. *The Quarterly journal of economics 124*(2), 843–881.

Fitzenberger, B., A. Osikominu, and R. Völter (2005). Imputation rules to improve the education variable in the iab employment subsample. *ZEW-Centre for European Economic Research Discussion Paper* (05-010).

Ganzer, A., A. Schmucker, P. Vom Berge, and A. Wurdack (2017). Sample of integrated labour market biographies–regional file 1975-2014. *FDZ-Datenreport 1*, 2017.

Georgiadis, G. (2015). Examining asymmetries in the transmission of monetary policy in the euro area: Evidence from a mixed cross-section global var model. *European Economic Review 75*, 195–215.

Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Gornemann, N., K. Kuester, and M. Nakajima (2016). Doves for the rich, hawks for the poor? distributional consequences of monetary policy.

Guvenen, F., F. Karahan, S. Ozkan, and J. Song (2015). What do data on millions of us workers reveal about life-cycle earnings risk? Technical report, National Bureau of Economic Research.

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

Hagedorn, M., J. Luo, I. Manovskii, and K. Mitman (2019). Forward guidance. *Journal of Monetary Economics 102*, 1–23.

Halvorsen, E., H. A. Holter, S. Ozkan, and K. Storesletten (2020). Dissecting idiosyncratic earnings risk. *Available at SSRN*.

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

Holm, M. B., P. Paul, and A. Tischbirek (2020). The transmission of monetary policy under the microscope. Federal Reserve Bank of San Francisco.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Kaplan, G., B. Moll, and G. L. Violante (2018). Monetary policy according to hank. *American Economic Review 108*(3), 697–743.

Patterson, C. et al. (2019). The matching multiplier and the amplification of recessions. In *2019 Meeting Papers*, Number 95. Society for Economic Dynamics.

Ravn, M. O. and V. Sterk (2017, oct). Job uncertainty and deep recessions. *Journal of Monetary Economics 90*, 125–141.

Rendahl, P. (2016). Fiscal policy in an unemployment crisis. *The Review of Economic Studies 83*(3), 1189–1224.

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

Werning, I. (2015). Incomplete markets and aggregate demand. Technical report, National Bureau of Economic Research.

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[13]) 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 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

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

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)

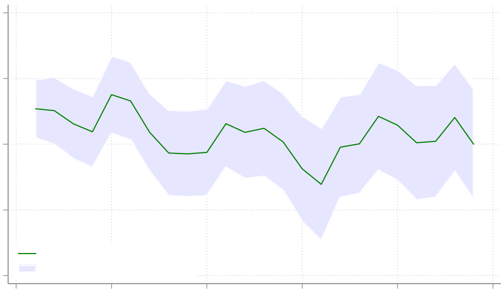
$$x_{t+h} - x_{t-1} = \alpha + \beta_h \Delta i_t + \gamma_h X_{t-1} + \varepsilon_{t,h} \tag{6}$$

where Δi_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, Δi_t and of x; lastly, it contains calendar month dummies.

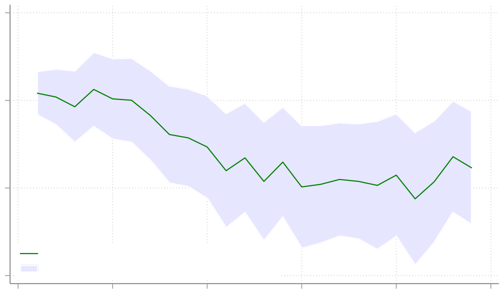
Figure 8 shows the impulse responses to a 25 basis point shock to the interest rate, estimated using Equation (6). The horizontal axis measures time after the monetary policy surprise in months, the vertical axis measures the percentage point change in the aggregate in question. The unemployment rate (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 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.,

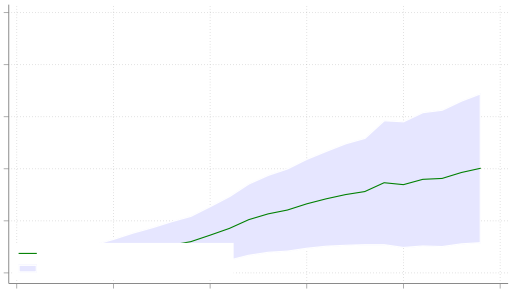
Figure 8: Aggregate responses to monetary policy surprises



(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 (6). 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.

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.