Who Gets Jobs Matters: Monetary Policy and the Labour Market in HANK and SAM*

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Abstract

This paper first provides empirical evidence that the labour market for the less educated, who also tend to be poorer, is substantially more volatile than the labour market for the well-educated, who tend to be richer. This is done by estimating job-finding rates by educational attainment for several European countries. These rates tend to be smaller and more volatile at lower education levels. We then construct a stylised HANK model augmented with search and matching and ex-ante heterogeneity in terms of the labour market. We show that monetary policy has stronger effects when the job market for less educated and hence poorer is more volatile. The reason is that poorer workers have the most procyclical income coupled with the highest marginal propensity to consume. After an expansionary monetary policy shock, their consumption increases strongly, causing aggregate consumption to increase by more. This fuels labour demand and feeds back to the increase in labour income of the poor, amplifying the initial effect. The same mechanism carries over to forward guidance.

JEL classification: E40, E52, J64

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1 Introduction

The distribution of wealth and the riskiness of income matter substantially for macroeconomic fluctuations in the standard heterogeneous agent New Keynesian (HANK) models (Kaplan et al. (2018)). An important concern in the literature has been the distribution of dividends, labour income and the incidence of taxation (Werning (2015), Broer et al. (2018), and Hagedorn et al. (2018)), with somewhat less emphasis on how labour income evolves over the business cycle for different households, even though labour income is typically the most important source of income for most households.

Labour literature tends to find that workers face very heterogeneous employment prospects and, thus, income risk over the business cycle. For example, Elsby et al. (2010) document that males, younger, less educated workers, and individuals from ethnic minorities experience steeper rises in unemployment during all recessions. Similarly, Patterson (2019) finds that earnings of individuals with higher marginal propensities to consume (i.e., young, black, and poor) are more exposed to recessions.[1] Relatedly, Haltiwanger et al. (2018) document that during the downturns, less educated and younger workers are more likely to exit to nonemployment and less likely to get out of nonemployment. Hoynes et al. (2012) come to a similar conclusion using individual-level Current Population Survey (CPS) and Merged Outgoing Rotation Group (MORG) data.[2] Workers with such characteristics are more likely to be poor. For example, in the Households Finance and Consumption Survey, the typical finding is that younger and less educated households are more likely to be credit constrained (see HFC (2016)).

Who is rich and who is poor matters in HANK models because households differ in terms of their marginal propensities to consume (out of wealth and out of income). In this setting, it is important whether household income (and income risk) is pro- or countercyclical because this matters for aggregate demand, which in turn matters for general equilibrium effects on households' incomes (see, e.g., Werning (2015), Acharya and Dogra (2018), Bilbiie (2018)). Moreover, it has been documented that economic policies may affect various segments of the wealth distribution differently, with the left tail typically being more strongly affected (Amberg et al. (2022) and Broer et al. (2022)). Using administrative data, Guvenen et al. (2017) investigate how individual earnings vary across wealth, but it is difficult to isolate the underlying structural reasons for their findings. Auclert and Rognlie (2018) use the results from Guvenen et al. (2017) to calibrate a function that rations labour of particular groups of households when wages are sticky, but the deeper underlying reasons why and who gets/loses jobs in the boom/recession have been less thoroughly investigated. One recent approach that provides more micro-foundations for heterogeneous labour market out-

[1] Mueller (2017) finds that during recessions, the pool of unemployed shifts towards high-wage workers. Elsby et al. (2015) observe similar regularity, and they attribute it to compositional effect; during recessions, the composition of the unemployment pool becomes skewed towards more attached individuals (i.e. male, prime-aged, more educated) because they are less likely to exit the labour force.

[2] Den Haan and Sedlacek (2014) develop a model where the least productive workers lose jobs first during the recession, and the most productive workers tend to get jobs first during the boom.

comes has been to use capital-skill complementarities (Dolado et al., 2021).

This paper first provides new empirical evidence on job finding rates by educational attainment for several European countries, which is novel to the best of our knowledge and is of independent interest. Empirical evidence suggests that job finding rates for the less educated and more likely poorer households are lower than for the better educated, are highly procyclical, and much more volatile. There are also considerable differences across European countries, with some where the labour market seems more homogeneous (with fewer differences by educational attainment) than in others. We report similar evidence for the US. Such evidence suggests that agents with low educational attainment face higher employment risk over the business cycle than agents with high educational attainment.

We then build a stylised model with the search and matching framework embedded in a HANK framework. The model considers the economy as composed of different labour market segments, where workers can either stay in the same market segment and face its income risk, or exogenously switch to another labour market segment, with different characteristics regarding wage fluctuations and (un)employment risk. These exogenous switches between labour market segments are rare but persistent and can be thought of as persistent changes in desirability for a particular skill.[3] Labour market segments differ with respect to wage level, job finding probabilities, and their cyclical properties. Each segment functions as a separate labour market with search and matching frictions. This means that each labour market segment has an endogenous job finding probability, which depends on firms' incentives to create vacancies in that segment, which in turn varies with economic conditions. The differences *between* labour market segments endogenously amplify income fluctuations caused by the idiosyncratic labour income risk for households (shifts from one labour market segment to the other). There are cyclical income fluctuations even for households that stay in the same labour market segment, because search frictions, combined with wage rigidities, imply that expected income *within* each labour market segment moves over the business cycle.

We use this framework to investigate the implications of such heterogeneous labour markets for monetary policy. We first show that if poor workers obtain jobs after a monetary expansion (which is consistent with empirical evidence), they tend to spend a larger proportion of the additional income, which amplifies aggregate demand, which in turn leads to more labour demand. If labour demand is again more oriented towards poorer households, then this works as an amplification mechanism, as it leads to even more consumption from the poor, making monetary policy more potent. What turns out to be important for the amplification is the asymmetry of the labour market, in the sense that the labour market segment of the poor reacts more procyclically than the labour market segments further to the right of the wealth distribution. We show that this can be brought about by two mechanisms that amplify vacancy posting in the labour market segment with lower educational attain-

[3]For instance, one can think of one incidence of such a switch looking at the data from a major job finding intermediary, Indeed (Adrjan (2019)). These indicate that upon the announcement that the plant of British Steel was scheduled to close, workers from that plant searched for jobs that were below their qualification level. That is, they searched for a job in what is effectively a different labour market segment.

ment. One such mechanism is a relatively low and hence more volatile firm surplus from hiring a worker from this labour market segment, and the other is a higher wage rigidity in the segment. Either or both lead to more volatile hiring for workers with lower educational attainment.

Our paper is most closely related to papers analysing economic fluctuations in heterogeneous agents models with labour market frictions (see for example Den Haan et al. (2017), Ravn and Sterk (2017)). However, our paper differs from the others in that we focus on the differences between labour market segments and their implications for shock transmission. Compared to Ravn and Sterk (2016), and Ravn and Sterk (2017), we consider the interplay between several labour market segments and allow agents to save. Den Haan et al. (2017) allows agents to save in two assets and solve the model fully globally, but they analyse a unified labour market. The paper perhaps closest to ours in terms of the setup of the labour market is Gornemann et al. (2016), however, they do not differentiate between labour market segments and focus mostly on systematic monetary policy and the distribution of incomes from assets and labour, while our focus is on labour market segments. Differently from Dolado et al. (2021), our model generates different labour market outcomes by only relying on labour market search frictions without capital-skill complementarity.

The remainder of the paper is structured as follows. Section 2 presents the empirical evidence on who obtains jobs and when. Section 3 describes the model, Section 4 discusses the results, and Section 5 concludes.

2 Who gets and who loses jobs

Employment outcomes of the well and less-well-educated workers can differ markedly over the business cycle. Education level can also serve as a proxy for income and wealth, and it has been shown that economic policies may affect households at a different point in the wealth distribution differently, e.g., by Amberg et al. (2022) or Broer et al. (2022). In this section, we first estimate job finding rates by educational attainment for several European countries and document their cyclical behaviour. We then provide similar evidence for the US.

2.1 Job finding rates by educational attainment in Europe

To estimate job finding rates by educational attainment, we use the data on unemployment spell duration by educational attainment, available in European Union Labour Force Survey (EU–LFS). In general, we follow the method by Shimer (2012), and its extension by Elsby et al. (2013). The difference compared to Elsby et al. (2013) is that we have quarterly data on the duration of unemployment, so we can more directly relate outflows from unemployment to Shimer's approach (which uses monthly data).[4]

[4] As pointed out by Elsby et al. (2013), there is an issue of duration dependence for data at a lower frequency. However, this is less of a problem for most Continental European countries, where Elsby et al. (2013) find no evidence for duration dependence.

Using the approach in Shimer (2012), the monthly change in unemployment can be written as follows

$$u_{t+1} - u_t = u_{t+1}^{<1} - F_t u_t, \tag{1}$$

where u_t is unemployment at monthly frequency, $u_{t+1}^{<1}$ is the stock of unemployed with unemployment duration of less than one month, and $F_t u_t$ is the flow out of unemployment. Rearranging and solving for outflow probability F_t, one obtains:

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^{<1}}{u_t}, \tag{2}$$

which can be used to get the (monthly) outflow hazard rate $f_t^{<1}$:

$$f_t^{<1} = -ln(1 - F_t). \tag{3}$$

The computation of this rate requires monthly data. However, as pointed out by Elsby et al. (2013), one can use data at lower frequencies, and this may be more convenient in labour markets that are less fluid than the US labour market, as is typically the case in Continental Europe. In particular, one can compute

$$F_t^{<d} = 1 - \frac{u_{t+d} - u_{t+d}^{<d}}{u_t}, \tag{4}$$

where d is the number of months, and compute the (monthly) outflow rate estimate as

$$f_t^{<d} = -ln(1 - F_t^{<d})/d. \tag{5}$$

We follow this approach, using quarterly data on unemployment by educational attainment collected by Eurostat, and LFS data on unemployment duration spells, also by educational attainment. We do so for $d = 3,\ 6,\ 12$, and for three levels of educational attainment: (1) Less than primary, primary, and lower secondary education, (2) Upper secondary and post-secondary non-tertiary, and (3) Tertiary education. We focus on large countries in Europe. The reason for this is twofold. First, we have relatively few observations for shorter unemployment spells due to the relatively less fluid labour markets in Continental Europe.[5] Second, the data is quarterly, and we distinguish by educational attainment, which further reduces the sample. This means that in smaller countries with a relatively small sample of the Labour Force Survey, we have only a few observations, especially in the group with the highest educational attainment. We focus on $d = 3$ in the main text but also report additional estimates for $d = 6$ and $d = 12$.

Table 1 reports quarterly job finding probabilities based on our estimates (Table 8 in appendix reports monthly hazard rates that can be compared to those in Elsby et al. (2013)). There are two main results that stand out in these estimates. First, there are considerable

[5]This has already been pointed out by Elsby et al. (2013).

Table 1: Quarterly job finding probabilities

		d=3			d=6			d=12		
Country	Sample	L	M	H	L	M	H	L	M	H
Germany	2005Q1-2019Q4	0.15	0.17	0.17	0.15	0.17	0.17	0.14	0.15	0.16
Greece	1998Q1-2020Q4	0.10	0.08	0.09	0.11	0.10	0.10	0.11	0.10	0.10
France	2003Q1-2020Q4	0.12	0.16	0.18	0.12	0.16	0.18	0.12	0.15	0.17
Italy	2001Q1-2020Q4	0.15	0.17	0.21	0.15	0.17	0.20	0.13	0.15	0.16
Spain	1998Q1-2020Q4	0.21	0.21	0.23	0.21	0.21	0.23	0.19	0.19	0.20
UK	2000Q1-2020Q2	0.14	0.19	0.21	0.15	0.19	0.21	0.13	0.17	0.18

Notes: The table reports quarterly job finding probabilities associated with the estimated monthly hazard rates, computed using the formula $p_t^W = 1 - exp(-3f_t)$, where p_t^W is the probability that an unemployed worker finds a job in the next quarter. L = Less than primary, primary, and lower secondary education, M = Upper secondary and post-secondary non-tertiary education, and H = Tertiary education. Values are sample averages.

differences across countries, with job finding probabilities ranging from 0.1 in Greece to 0.2 in Spain. Second, the probability of finding a job rises with educational attainment and is the highest for those with the highest educational attainment (H). However, there are exceptions, such as Greece, where the level of educational attainment does not seem to correlate with the job finding probability in our sample.[6]

Further characteristics that are of interest are the volatility and cyclical behaviour of the estimated job finding rates. Table 2 reports the standard deviation and correlation with the total unemployment rate of the cyclical components of the estimated job finding rates.[7] Three characteristics stand out. First, the job finding rates of the least educated (L) are highly volatile, and much more volatile than the job finding rates at higher levels of education (note that the highest level, H, is quite volatile mainly because of very small samples for this segment, so the results should be interpreted with caution).[8] Second, job finding rates at all educational levels are procyclical (they are negatively correlated with unemployment). Third, there is considerable heterogeneity across countries regarding the cyclical properties by educational attainment. In Germany, the M and H educational levels are almost acyclical, while in the UK and Italy, L is almost acyclical.

The findings reported above are broadly in line with the empirical evidence for Europe. Slacalek et al. (2020) suggests that, based on unconditional estimates, the elasticities of employment responses of hand-to-mouth households, and in particular of poor hand-to-mouth households, tend to be large. While the estimates vary across countries, the sensitivity of employment of poor hand-to-mouth households is at least 1.5-times larger than the aggre-

[6] This may be due to public-sector employment reductions during the sovereign debt crisis, which might have affected relatively more educated workers in the public sector, although we cannot verify this based on our data.

[7] Cyclical components were obtained using the Hodrick-Prescott filter with the smoothing coefficient of 1600. Before filtering, 4-quarter moving averages were computed to reduce the seasonal fluctuations in job finding rates and unemployment rates.

[8] While we do not emphasise this aspect here, job finding rates for the least educated tend to also be highly seasonal, especially in countries of Southern Europe. This is another indication that this segment of the labour market features more risky jobs than the other segments.

Table 2: Cyclical properties of quarterly job finding probabilities

	Volatility			Corr. with unemployment		
Country	L	M	H	L	M	H
Germany	10.20	7.16	12.09	-0.45	-0.21	-0.06
Greece	61.43	39.32	53.18	-0.41	-0.50	-0.39
France	16.57	11.91	12.16	-0.56	-0.24	-0.48
Italy	13.87	11.85	13.30	-0.28	-0.46	-0.49
Spain	10.69	11.91	11.11	-0.68	-0.74	-0.82
UK	15.17	11.04	11.63	-0.11	-0.36	-0.25

Notes: The table reports volatility of the cyclical component of monthly hazard rates (as standard deviation), and the correlation with the cyclical component of total unemployment, all based on $d = 3$ estimates. L = Less than primary, primary, and lower secondary education, M = Upper secondary and post-secondary non-tertiary education, and H = Tertiary education.

gate employment. A similar finding is reported by Dossche and Hartwig (2019), who look at worker betas across the income distribution and find significantly higher worker betas in the lowest household income quintile. This elasticity can be up to four times higher in the lowest quintile than in the highest quintile. Empirical evidence *conditional* on a monetary policy shock (Lenza and Slacalek (2018) and Broer et al. (2022)) also suggests that in Europe, incomes of poor households tend to react more strongly to a monetary policy than the incomes of wealthier households.

2.2 Evidence from the US

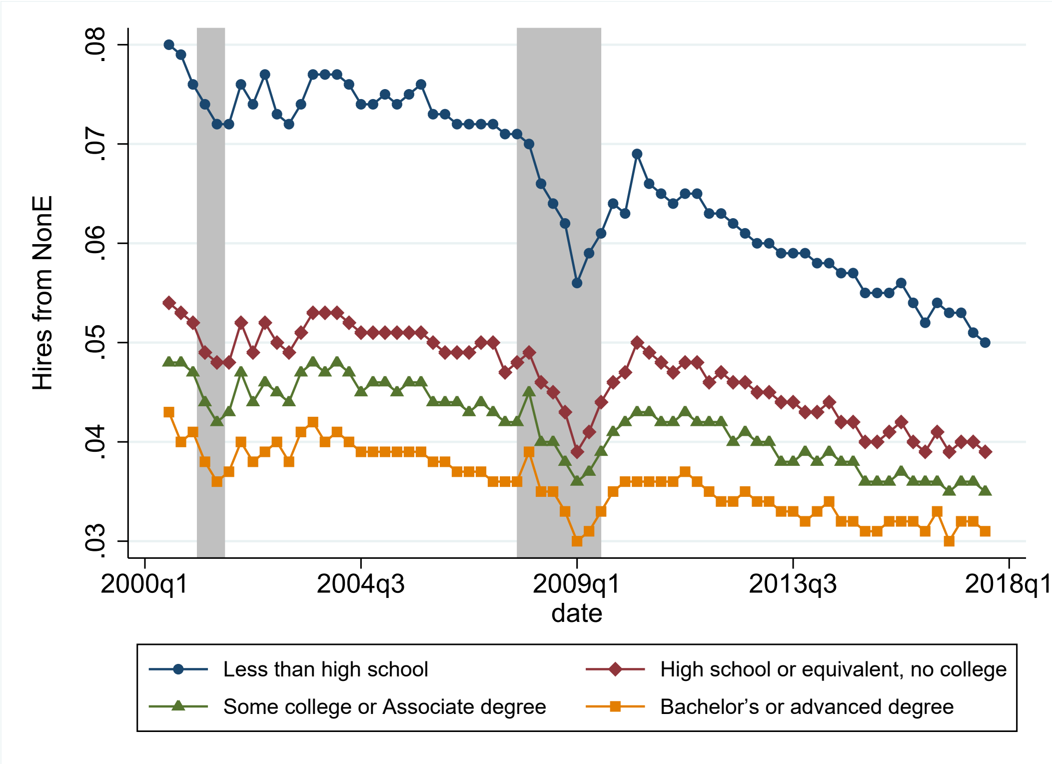
For the US, we have somewhat more detailed data available. We use publicly available Longitudinal Employer-Household Dynamics (LEHD) data from the US Census Bureau. The LEHD database is constructed from various administrative sources, such as Quarterly Census of Employment and Wages, Unemployment Insurance earnings data, surveys and censuses. All the data we use are quarterly, seasonally adjusted and cover period between 2000 Q2 and 2017 Q3. If not otherwise stated, (net) hires and separations are expressed as a share of employment.

Figures 1a and 1b plot hires from, and separations to, persistent nonemployment across education groups. One can observe that the hiring rate and separation rate are inversely related to educational attainment, i.e., less educated workers have larger inflow and outflow rates to persistent nonemployment.

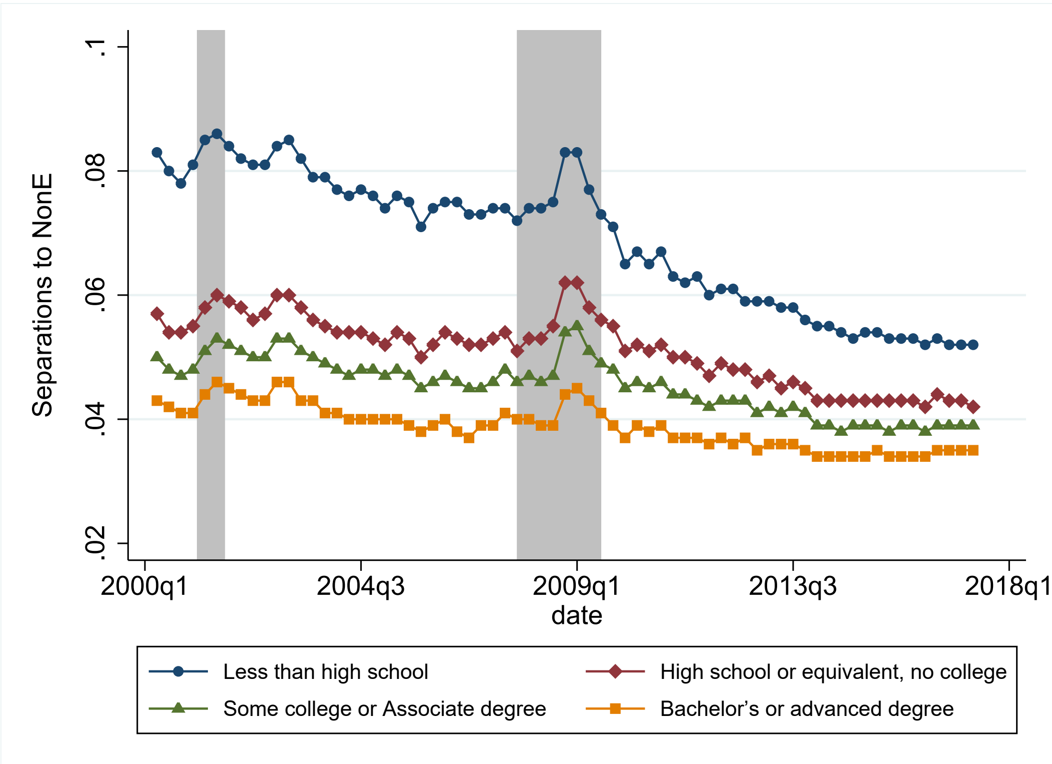
To get a clearer picture of who is more affected by business cycle fluctuations, we look at the difference between the two rates. Figure 2 shows net worker flows—hires minus separations—by educational attainment. It shows that during the recession, net hiring for the group of workers with the lowest educational attainment declined much more than for the group with the highest educational attainment; during downturns, the less educated segments of the labour market experience more adverse developments than segments for the

Figure 1: Hires and Separations to persistent nonemployment

(a) Hires



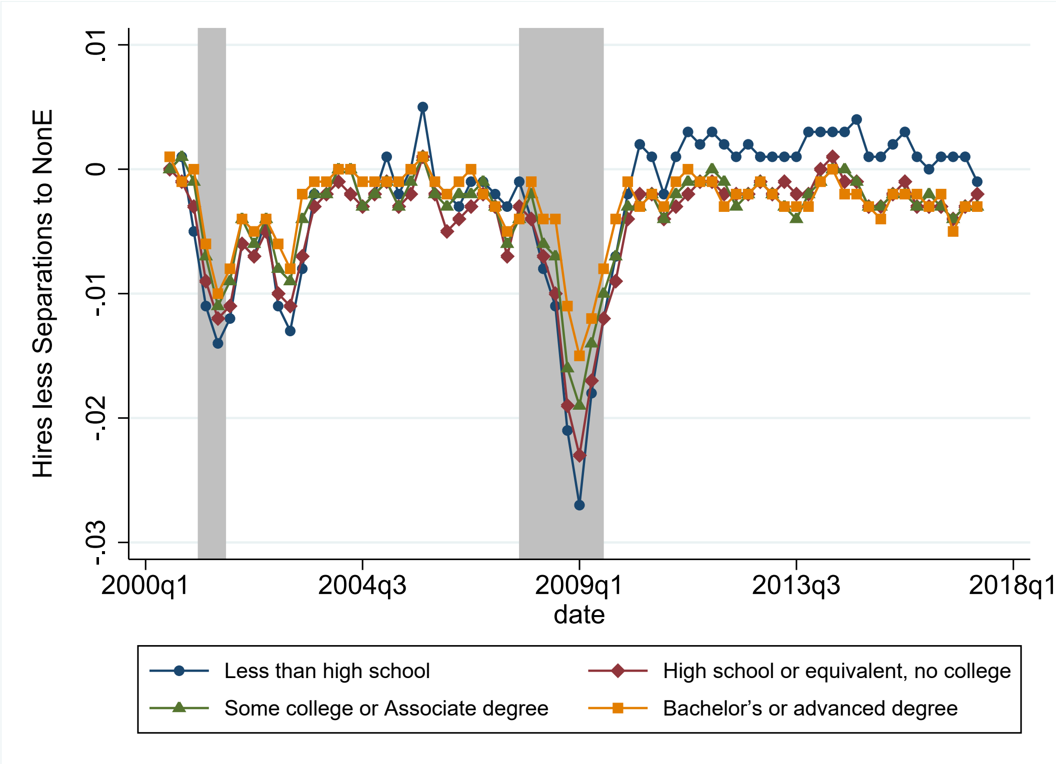
(b) Separations



Notes: A worker is defined as being a *Hire from Persistent Nonemployment* in quarter *t*, if she or he had no main job in the beginning of the quarter *t-1* and *t*, but had one at the end of quarter *t*. A worker is defined as undergoing a *Separation to Persistent Nonemployment* in quarter *t*, if she or he, had a main job in the beginning of quarter *t*, and not at the end of quarter *t* or quarter *t+1*. Everything is expressed as a share of an average employment within the education group. Shaded areas denote NBER recessions.

more educated. This pattern is particularly notable during the Great Recession when the net hiring for the group with less than high school dropped by more than twice as much as for the group with the bachelor's or higher degree. While less extreme, the same pattern is observed during the milder 2001 recession.

Figure 2: Net hires from persistent nonemployment



Notes: Net hires is calculated as the difference between hires from and separations to persistent nonemployment, and it is expressed as a share of an average employment within the education group. Shaded areas denote NBER recessions.

Notably, at the onset of recovery, the net hiring in the groups with the lowest educational attainment is also the one that exhibits the largest jump upwards. Again the pattern is such that the upward jumps are more extreme for less educated groups, and the magnitudes of the increases decrease with education. This indicates that the groups with lower education, while being those that are most exposed to the net job loss in the recession, are also the groups who are the most exposed to net job gain when the recession is over.

Table 3 shows summary statistics for our sample. Less educated workers experience larger inflow and outflow rates to nonemployment, and these rates are also more volatile. This confirms that less educated workers face a higher risk of going to, or coming from, nonemployment. For example, the rate of hires and separations for the workers in the lowest education group is two to three times larger than for the workers in the highest education group, and the volatilities of these rates are about three times higher for the least educated than for the most educated.

With the LEHD data, we, unfortunately, cannot calculate job finding rates, but only their *proxies* across education groups. The reason is that a job finding rate is defined as a ratio of unemployed workers who find a job over the number of unemployed. However, in the LEHD data, we observe only hires from nonemployment, which is a broader concept than unemployment, as it also includes workers who are not in the labour force. Nevertheless, we report these "rates" in the last row of Table 3, as they at least give some notion of the ranking of these rates between education groups. Note that these proxies for job finding rates are increasing with educational attainment (except for the group of less than high school, but this group is very small in the data).

Table 3: Summary statistics

	Less than high school		High school or equivalent, no college		Some college or Associate degree		Bachelor's degree or advanced degree	
	mean	sd	mean	sd	mean	sd	mean	sd
Hires	0.066	0.0084	0.046	0.0043	0.041	0.0038	0.035	0.0032
Separations	0.069	0.011	0.051	0.0056	0.045	0.0045	0.038	0.0035
Hires less Separations	-0.0025	0.0062	-0.0042	0.0045	-0.0035	0.0037	-0.0029	0.0030
Job finding rate proxy	0.782	0.218	0.614	0.187	0.714	0.294	0.776	0.350

Notes: (Net) hires and separations are rates and are expressed as a share of an average employment within the education group.

To further investigate whether workers with low(er) educational attainment face larger countercyclical employment risk, we estimate the following equation:

$$Y_{i,t} = \gamma_t + \beta_1 \, educ_i + \beta_2 \, educ_i \times X_t + \epsilon_{i,t}, \tag{6}$$

where $Y_{i,t}$ is either the (net) hire or separation rate, X_t is the cyclical component of GDP,[9] $educ_i$ is workers' educational attainment, γ_t are time dummies to control for common shocks, and $\epsilon_{i,t}$ is the residual term. What we are interested is the coefficient on the interaction term, which measures the differential responsiveness - across education groups - of net hiring rate to a business cycle. Note that results have to be interpreted relative to the highest education group.[10]

Table 4 reports the results from estimating Equation 6. Column 1 shows that the net hiring rate of less educated workers is more sensitive to business cycles than the net hiring rate of workers with the highest level of educational attainment. This implies that (countercyclical) employment risk is largest for the least educated workers, and it falls with increasing educational attainment. Results are in line with Haltiwanger et al. (2018), who find that during recessions, workers with lower education are more likely to exit to nonemployment. They also find that conditional on firm productivity groups, hires and separations are more cyclically sensitive for less educated workers. In columns 2 and 3, we separate the net hiring rate into hires and separations to see which margin is more important. We find that only hires are significantly different across education levels; the hiring rate for the least educated

[9] We obtain it after applying the Hodrick-Prescott filter to a logarithm of seasonally adjusted real GDP. In Appendix B.2, we also consider other measures of business cycle, i.e NBER recession episodes and the cyclical component of the level of unemployment. The results do not materially change.

[10] That is, relative to workers with bachelor's degree or advanced degree.

Table 4: Worker flows over the business cycle

VARIABLES	(1) Net hires	(2) Hires	(3) Separations
Less than high school	0.000	0.030***	0.030***
	(0.000)	(0.001)	(0.001)
High school or equivalent, no college	-0.001***	0.011***	0.012***
	(0.000)	(0.000)	(0.000)
Some college or Associate degree	-0.001**	0.006***	0.007***
	(0.000)	(0.000)	(0.000)
Less than high school × GDP cycle	0.123***	0.079**	-0.018
	(0.036)	(0.037)	(0.056)
High school or equivalent, no college × GDP cycle	0.070***	0.018	-0.044
	(0.024)	(0.019)	(0.029)
Some college or Associate degree × GDP cycle	0.037	0.003	-0.031
	(0.025)	(0.020)	(0.032)
Time FE	X	X	X
Observations	272	276	276
R-squared	0.9028	0.9713	0.9468

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: (Net) hires, and separations are rates and are expressed as a share of an average employment within the education group.

workers is more cyclically sensitive than for the workers with the highest education.[11] In Appendix Table 11, we also estimate the sensitivity of changes in (net) hires and separation rates to changes in GDP across education groups. Results confirm our previous findings that changes in (net) hiring rates of workers with lower education tend to be more sensitive to changes in GDP, implying that they face larger employment and, therefore, income risk than more educated workers.

2.2.1 Wage rigidity

For the US, we also have some evidence of differential wage rigidity across educational attainment levels, which we lack for European countries.

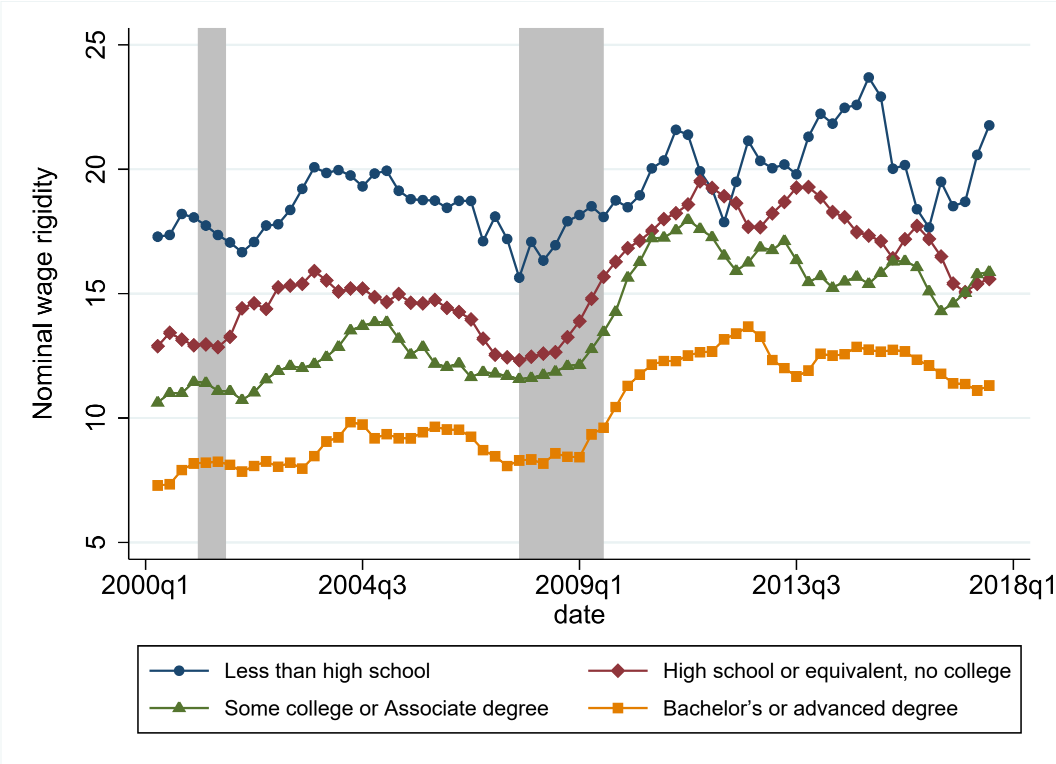
Figure 3 plots the data from the matched Current Population Survey dataset (see Daly et al. (2012)). The figure shows the percentage of workers who reported no change in their wages over the past year by educational attainment. It shows that wages of less educated workers tend to be stickier than wages of more educated workers. This regularity holds over all business cycle phases and over a long time span.[12] While these data do not cover new hires, they indicate that labour market segments by educational attainment have different properties. More recent evidence of differential wage rigidity for *new hires* across education

[11] Interestingly, when we run regression on NBER recession episodes (see Table 9 in Appendix B.2), we find a statistically significant difference in separation rates among education groups; low educated workers have larger separation rates during downturn(s) relative to highly educated workers.

[12] See Figure 10 in Appendix for the full sample.

levels is Doniger (2019), who finds (i) wages for new hires of least educated workers to be acyclical, and that (ii) wage (pro)cyclicality increases with the educational attainment. She also finds that after a monetary policy shock, less educated workers respond on the employment margin while the more educated respond on the wage margin.[13]

Figure 3: Wage rigidity by educational attainment



Notes: Percentage of workers who saw no change in their wage over the past year by educational attainment. Source: https://www.frbsf.org/economic-research/indicators-data/nominal-wage-rigidity/

3 Model

The core of the model is the by now standard heterogeneous agents New Keynesian model of McKay and Reis (2016) and McKay et al. (2016). To account for the different labour market prospects faced by individual households, we modify their model so that each labour income level has its own labour market segment.

We assume that each labour market segment is populated by a continuum of households and a continuum of labour firms. Labour firms post vacancies and households decide how many workers to send searching for jobs. Job search is subject to search frictions, and firms and households take matching probabilities as given when deciding on how many vacancies to post or how many workers to send to the market.

[13]In contrast, Haefke et al. (2013) and Kudlyak (2014) find no evidence of nominal wage rigidity for new hires, however as pointed out by Doniger (2019), they do it for representative agent and do not differentiate across educational attainment.

Markets are incomplete, and there is heterogeneity *between* households, but full insurance *within* each household. Each household consists of a continuum of workers who have the same level of labour productivity and can be either employed or unemployed. At the end of each period, workers bring their incomes home and the household as a whole decides on how much to consume and save, subject to prices and job finding probabilities. This simplification allows us that, within a household type, we can use the average rates of employment, unemployment, matching probabilities, and wages. In addition, if there are no unemployment benefits available, this assumption also prevents households with no assets from having zero consumption. Note that this assumption still preserves the cyclical risk of household income as a whole.

The household sends its workers to search for work at the beginning of each period. They either find work, in which case they bring home earnings, or they remain unemployed and receive unemployment benefits (if any). At the end of the period, all jobs terminate, and the search starts again in the next period. This assumption allows us to avoid an additional state variable (employment) for each labour market segment. Because we have three labour market segments, this would add three additional endogenous state variables to the already existing one endogenous (asset holdings) and one exogenous (labour productivity process). Note that even in this case, the persistence of employment is implied by the job finding probability in the labour market segment. That is, in segments with higher job finding probabilities, employed workers are more likely to remain employed, even if they separate every period, because they are more likely to find a new job at the beginning of the next period. That is, we can mimic income risk in each labour market segment by adjusting the job finding probability.

The remainder of the model is similar to McKay et al. (2016). In the main text, we only report the equations we modified to include the search and matching frictions on the labour market into the model, while the remaining equations are reported in Appendix C. The economy is populated by a continuum of ex-ante identical households who face the following decision problem:

$$V_t(b_{h,t}, z_{h,t}) = \max_{c_{h,t}, b_{h,t+1}, s_{h,t}, l_{h,t}, u_{h,t}} \left\{ \frac{c_{h,t}^{1-\gamma}}{1-\gamma} - \eta_1 \frac{s_{h,t}^{1+\eta_2}}{1+\eta_2} + \beta \sum_{z_{h,t+1}} P\left(z_{h,t+1} | z_{h,t}\right) V_{t+1}(b_{h,t+1}, z_{h,t+1}) \right\}$$

subject to

$$c_{h,t} + \frac{b_{h,t+1}}{1+r_t} = b_{h,t} + Bu_{h,t} + w_{h,t} l_{h,t} - \tau_{z_h,t} + \Pi_{z_h,t}, \tag{7}$$

$$s_{h,t} = l_{h,t} + u_{h,t}, \tag{8}$$

$$l_{h,t} = p^W_{z_h,t} s_{h,t}, \tag{9}$$

$$u_{h,t} = (1 - p^W_{z_h,t}) s_{h,t}, \tag{10}$$

and

$$b_{h,t+1} \geq 0. \tag{11}$$

Here, $c_{h,t}$ is consumption of household h at time t, $b_{h,t}$ are its bond holdings at time t, r_t is the real interest rate, $s_{h,t}$ is the number of searching workers within household h at time t, $l_{h,t}$ is the number of employed workers within household h at time t, $u_{h,t}$ is the number of unemployed workers within household h at time t, $w_{h,t}$ is the real wage, and B are unemployment benefits. $\tau_{z_h,t}$ are taxes (levied as lump-sum depending on the household's labour endowment, and $\Pi_{z_h,t}$ are profits from intermediate goods firms and labour firms.[14] $P\left(z_{h,t+1}|z_{h,t}\right)$ is the (exogenous) probability of transitioning between labour market segments, and it follows a Markov process. The households take prices, taxes, dividends, and unemployment benefits as given.

We assume that all intermediate goods firms and labour firms are held by an investment fund managed by a risk-neutral manager, who collects profits and distributes them as dividends to households (i.e., households cannot trade in equities). Households are allowed to save by holding and trading bonds issued by the government. These bonds are in positive and constant net supply, so households can partially self-insure by saving.

A household's optimisation gives the following first-order conditions with respect to the choice variables

$$c_{h,t}{}^{-\gamma} - \lambda_{h,t} = 0, \tag{12}$$

$$-\frac{c_{h,t}{}^{-\gamma}}{1+r_t} + \beta \sum_{z_{h,t+1}} P\left(z_{h,t+1}|z_{h,t}\right) V'_{t+1}(b_{h,t+1}, z_{h,t+1}) = 0, \tag{13}$$

$$-\eta_1 s^{\eta_2}_{h,t} + p^W_{h,t} q_{h,t} - \mu_{h,t} + (1 - p^W_{h,t})\xi_{h,t} = 0, \tag{14}$$

$$-q_{h,t} + \mu_{h,t} + \lambda_{h,t} w_{h,t} = 0, \tag{15}$$

$$-\xi_{h,t} + \mu_{h,t} + \lambda_{h,t} B = 0, \tag{16}$$

where $\lambda_{h,t}$ is the multiplier on (7), $\mu_{h,t}$ on (8), $q_{h,t}$ on (9), and $\xi_{h,t}$ on (10).

By eliminating the Lagrange multiplier on the budget constraint and applying the envelope theorem, we get the standard Euler equation

$$c_{h,t}{}^{-\gamma} = \beta(1+r_t) \sum_{z_{h,t+1}} P\left(z_{h,t+1}|z_{h,t}\right) \left(c_{h,t+1}{}^{-\gamma}\right). \tag{17}$$

[14] We assume that profits from labour firms are given as lump-sum but in proportion to employment.

Rearranging (12), (14), (15) and (16) delivers

$$\frac{\eta_1 s_{h,t}^{\eta_2}}{c_{h,t}^{-\gamma}} = p_{h,t}^W w_{h,t} + (1 - p_{h,t}^W)B, \tag{18}$$

which says that in equilibrium, the disutility of searching (measured in monetary terms) has to be equal to the expected earnings from searching. The latter are weighted average of the expected real wage and unemployment benefits, where the weight is the probability of getting a job.

3.1 Labour market

Labour market segments There is a separate labour market for each productivity type of households (in total, there are three labour market segments). On each labour market segment, indexed by the productivity type z_h, we have a separate matching function and matching probabilities:

$$m_{z_h,t} = \phi_{z_h} s_{z_h,t}^{\mu_{z_h}} v_{z_h,t}^{1-\mu_{z_h}}, \tag{19}$$

where $m_{z_h,t}$ is the number of matches in the market z_h, ϕ_{z_h} is the labour-market-segment-specific matching efficiency, $s_{z_h,t}$ is the number of searching workers, and $v_{z_h,t}$ is the number of vacancies. μ_{z_h} is the elasticity of the matching function with respect to the number of searching workers.

The matching probability for the worker, $p_{z_h,t}^W$, is

$$p_{z_h,t}^W = \frac{m_{z_h,t}}{s_{z_h,t}} = \phi_{z_h} \left(\frac{v_{z_h,t}}{s_{z_h,t}} \right)^{1-\mu_{z_h}} = \phi_{z_h} \left(\theta_{z_h,t} \right)^{1-\mu_{z_h}}, \tag{20}$$

and the matching probability for the firm, $p_{z_h,t}^F$, is

$$p_{z_h,t}^F = \frac{m_{z_h,t}}{v_{z_h,t}} = \phi_{z_h} \left(\frac{v_{z_h,t}}{s_{z_h,t}} \right)^{-\mu_{z_h}} = \phi_{z_h} \left(\theta_{z_h,t} \right)^{-\mu_{z_h}}. \tag{21}$$

Households Households send workers to search until the cost of searching (measured in monetary terms) is equal to the expected earnings from searching. For a household with a productivity level z_h, this implies

$$\eta_1 \frac{(l_{h,t} + u_{h,t})^{\eta_2}}{c_{h,t}^{-\gamma}} = p_{z_h,t}^W w_{z_h,t} + (1 - p_{z_h,t}^W)B, \tag{22}$$

where $(l_{h,t} + u_{h,t})$ is the total amount of workers the household sends in the beginning of the period to the labour market to search for jobs, $c_{h,t}^{-\gamma}$ is the marginal utility of consumption, $p_{z_h,t}^W$ is a fraction of workers who find a job and earn real wage $w_{z_h,t}$, and $(1 - p_{z_h,t}^W)$ is a fraction of workers who do not find a job, but receive unemployment benefits B.[15]

[15]Equation (22) also nests standard labour supply model; if $p_{z_h,t}^W = 1$, so that everyone finds a job (implying

The setting of the model makes it clear where the sources of income fluctuations come from. The first source, which is due to idiosyncratic labour productivity shocks that shift households between labour market segments, is acyclical. These shocks can be thought of as shocks that make a particular skill either more sought-after or less desired on the market.[16] This type of risk is fully taken into account by the households in our model. The second type of income fluctuation in our model is cyclical and comes from different labour market conditions in labour market segments. These conditions depend on the state of the business cycle and, in our model, differ across the labour market segments. Because the risk associated with the cyclical fluctuations is aggregate, it is not taken into account by the households in our model. It does, however, affect their income so that their decisions (and aggregate outcomes) depend on the income fluctuations of individual households.

Labour firms We assume that each productivity segment of the labour market is a separate labour market with its own labour firms. Labour firms hire workers and sell their effective labour as a homogeneous good at a competitive aggregate wage ω_t to the intermediate-goods firms.[17] Each labour firm employs one worker. The value function of the labour firm is

$$J_{z_h,t} = \omega_t z_{h,t} - w_{z_h,t}, \tag{23}$$

where $\omega_t z_{h,t}$ is the total revenue received by the labour firm from selling labour services (one worker provides labour services corresponding to his productivity $z_{h,t}$, which is sold to the intermediate-goods firm at the rate ω_t). The labour firm pays the worker real wage $w_{z_h,t}$ and returns profits to the household as lump-sum.

The free-entry condition for labour firms is

$$\psi_{z_h} = p^F_{z_h,t} J_{z_h,t}, \tag{24}$$

where ψ_{z_h} is the vacancy posting cost in the labour market segment with productivity z_h. In equilibrium, the labour firm's optimality condition states that the cost of posting a vacancy in the beginning of the period is equal to the probability that the firm will find a worker, times the value of that worker for the firm (which is equal to the profit the firm will earn in this period).

Wage determination We consider two settings for wages. When wages are fully flexible, we assume that the wage rate that is paid to the workers in each segment is a fraction $(1 - \alpha_{z_h})$ of the aggregate wage cost:[18]

$u_{h,t} = 0$), and $B = 0$, it reduces to the standard labour supply condition.

[16] For example, automation in some industries have made workers with skills that can be automated less sought-after, and workers who can program the machinery used for automation of these jobs more sought-after.

[17] Alternatively, one can also think of labour firms as intermediaries who solve the hiring problem for intermediate-goods firms.

[18] Equivalently, this can be also seen as a revenue of labour firms.

$$w_{z_h,t} = (1 - \alpha_{z_h})\omega_t z_{h,t}. \tag{25}$$

The aggregate wage cost is determined in equilibrium as the cost that equates the labour demand from intermediate goods firms with the labour services' supply from labour firms (and therefore labour supply from households).

When we analyse a setting with rigid wages, we follow Hall (2005) and model wage rigidity as a weighted average of the wage that would be determined in the current period (as described above), and a wage norm. For the wage norm we take the steady-state wage.[19] We allow wage rigidity to differ across labour market segments. The rigid wage is then

$$w_{z_h,t} = [(1 - \omega_R)(1 - \alpha_{z_h})\omega_t + \omega_R(1 - \alpha_{z_h})\overline{\omega}]z_{h,t}, \tag{26}$$

where $\omega_R \in [0, 1]$ is the weight of the wage norm, and $(1 - \alpha_{z_h})\overline{\omega}$ is the wage norm.

Nash bargaining Additionally, we also consider Nash bargaining where the wage is the outcome of bargaining between workers and firms how to split the total surplus generated by a successful match. The solution to Nash bargaining problem is

$$\chi_{z_h} J_{z_h,t} = (1 - \chi_{z_h})(W^E_{z_h,t} - W^N_{z_h,t}), \tag{27}$$

where $\chi_{z_h} \in (0, 1)$, is the bargaining power of the worker that can be labour-market-segment-specific,[20] $J_{z_h,t}$ is the value of a job for a firm, and $W^E_{z_h,t}$, $W^U_{z_h,t}$ are the value functions of being employed and unemployed. The value functions for a firm and a worker are

$$J_{z_h,t} = \omega_t z_{h,t} - w_{z_h,t}, \tag{28}$$

$$W^E_{z_h,t} = w_{z_h,t} - \eta_1 \frac{(l_{h,t} + u_{h,t})^{\eta_2}}{c_{h,t}^{-\gamma}}, \tag{29}$$

$$W^U_{z_h,t} = B - \eta_1 \frac{(l_{h,t} + u_{h,t})^{\eta_2}}{c_{h,t}^{-\gamma}}. \tag{30}$$

To get the wage equation, one substitutes (28), (29), and (30) into (27) yielding

$$w_{z_h,t} = \chi_{z_h}(\omega_t z_{h,t} - B) + B, \tag{31}$$

which means that the bargained wage a worker receives is equal to the outside option (in our case unemployment benefits) and a fraction (χ_{z_h}) of the surplus from a successful match. Note that the larger the χ_{z_h}, i.e. the larger the bargaining power of the worker, less "sticky" is the real wage. If we set $B = 0$, so that there are no unemployment benefits, and define

[19] This allows us to avoid introducing past wage as an additional state variable.

[20] With $\chi_{z_h} = 1$, firms would have zero profits (all the surplus goes to workers), but would still have to pay positive vacancy posting costs which prevents them from posting vacancies.

$\chi_{z_h} \equiv (1-\alpha_{z_h})$, we get exactly (25).

Finally, in order to see how the wage depends on the labour market developments, we substitute (24) and (21), together with (29), and (30) into (27) to obtain

$$w_{z_h,t} = \frac{\chi_{z_h}}{1-\chi_{z_h}} \left(\frac{\psi_{z_h}}{\phi_{z_h}} (\theta_{z_h,t})^{\mu_{z_h}} \right) + B, \tag{32}$$

which states that the negotiated wage is increasing in bargaining power of the worker (χ_{z_h}), vacancy posting cost (ψ_{z_h}), labour market tightness ($\theta_{z_h,t}$), and decreasing in matching efficiency (ϕ_{z_h}) .

3.2 Calibration

The model is quite stylised and we largely rely on standard values from the literature to calibrate it. However, for the labour market, we do match some of the properties reported in the empirical section of the paper. In particular, we calibrate the model to match job finding rates by educational attainment and their relative volatility. We also perform several experiments illustrating how the model properties depend on the calibration choices.

The calibration of production and utility functions follows McKay et al. (2016), and is reported in Table 5.

Table 5: Utility function and production function

	Parameter	Value
Risk aversion	γ	2
Frisch elasticity (inverse)	η_2	2
Disutility weight for labour	η_1	1
Markup	μ	1.2
Price rigidity	θ	0.15

Idiosyncratic risk of transiting from one labour market segment to the other is also calibrated using the transition matrix from McKay et al. (2016) who use the persistent component of wage process from Floden and Lindé (2001), approximated using a 3-state Markov process with the transition matrix

$$P = \begin{bmatrix} 0.966 & 0.034 & 0 \\ 0.017 & 0.966 & 0.017 \\ 0 & 0.034 & 0.966 \end{bmatrix}$$

This matrix gives rise to the population shares $[0.25 \quad 0.5 \quad 0.25]$, for each labour market segment, "poor", "middle", and "rich". These transition probabilities do not vary over the business cycle so that the mass of households in each segment is constant.

The calibration of the labour market is reported in Table 6. Labour endowment corresponds to the level of wages in each labour market segment and follows McKay et al.

(2016). The differences in wage level also give rise to differences in the wealth distribution, which reflects, to some extent, the differences in the wage level (hence the labels "poor", "middle", and "rich"). The calibration of matching elasticities relies on the standard values from Petrongolo and Pissarides (2001). Since wages in Continental Europe and in Germany are fairly rigid, we assumed that there is a degree of wage rigidity across all labour market segments.[21]

We use the calibration of the entrepreneur's share and the vacancy posting cost to match the job finding probability for the typical case where this probability increases by educational attainment. We have picked the values that very closely correspond to the values found for Germany (see Table 1). Because the job finding rate depends on the ratio of vacancy posting cost and the entrepreneur's share, we could have fixed one and used the other to match the job finding probability. However, we wanted also to match the relative volatility of the labour market segments, which in Germany are much more volatile and much more procyclical for the low-educated (see Table 2). To do so, we follow the idea in Hagedorn and Manovskii (2008), who propose to solve the puzzle of too small volatility of labour market variables in the standard search-and-matching model (see Shimer (2005)) by calibrating the entrepreneur's share to be small. We set the entrepreneur's share to be smaller in the labour market segment with the lowest educational attainment, where we observe higher labour market volatility, and then adjust the vacancy posting cost to match the job finding probability.

While modelled on Germany, this calibration is meant to represent the typical case found in the data for European countries. There are, however, countries such as Spain where there seem to be fewer differences in terms of volatility and cyclicality between different labour market segments (Table 2). To illustrate the difference this makes, we also report simulations for the recalibrated model, where labour market segments are similar. We do this by matching job finding rates for Spain (0.20 for each labour market segment) and by equalising entrepreneurs' share across labour market segments (at 0.05), which makes labour firms' surplus and hence vacancy posting equally cyclical for all segments of the labour market.

Table 6: Matching function and labour firms, calibration to Germany

	Parameter	Poor	Middle	Rich
Labour endowment	z_h	0.4923	1.0000	2.0313
Matching elasticity	μ_{z_h}	0.5	0.5	0.5
Matching efficiency	ϕ_{z_h}	0.6	0.6	0.6
Vacancy posting cost	ψ_{z_h}	0.01	0.11	0.37
Entrepreneur's share	α_{z_h}	0.01	0.06	0.11
Wage rigidity	ω_R	0.5	0.5	0.5
Job finding probability	p^W	0.14	0.16	0.18

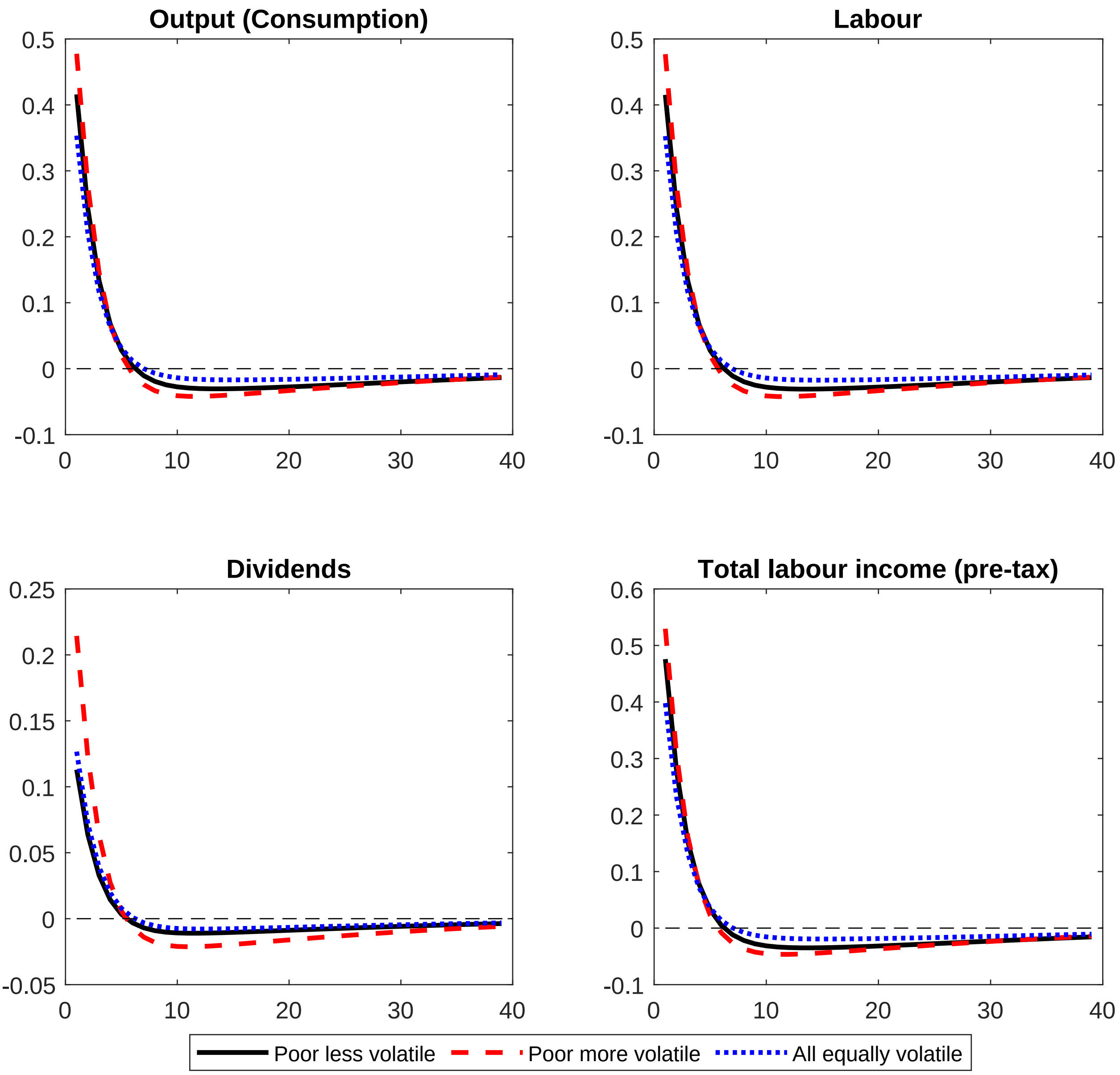
[21]Our choice of wage rigidity calibration implies that wages adjust only by half of what they would if they were flexible.

4 Results

4.1 Calibration for European countries

We first simulate a standard monetary policy shock, where the central bank temporarily raises the real interest rate by half a percentage point.[22] The results are reported in Figures 4 to 6.

Figure 4: Effectiveness of monetary policy depending on who gets jobs



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

[22] We follow McKay et al. (2016) and assume that because prices are sticky, a central bank can directly control the real interest rate in the short run. We, therefore, use a lower persistence, 0.6, for the AR(1) process governing the shock.

Figure 4 reports aggregate results. The red dashed line represents our benchmark calibration in Table 6, where the labour market segment for the less educated (”poor”) households is calibrated to be more volatile than the other labour market segments, in line with the data for Germany. For comparison, the full black line shows the case where the labour market for the less educated is only half as volatile as the benchmark case (but still more volatile than the other two labour market segments).[23] Everything else is kept the same, which allows us to discuss the implications of labour market volatility for aggregate fluctuations. Finally, we also plot a case that would correspond to countries like Spain, where empirical evidence indicates that both job finding probabilities and the volatility across labour market segments are very similar (shown in a dotted blue line).

The key property to note is that aggregate fluctuations tend to be amplified when the labour market segment of the poor is more volatile. Initial output response is, for instance, 17% higher for the red dashed line (compared to the black line), and this is similar for aggregate labour and labour income responses. The difference in the magnitude of responses are even larger when compared to the symmetric case. Dividends are procyclical due to sticky wages.[24]

To understand the mechanism behind this result, it is instructive to look at disaggregated quantities. Figure 5 and 6 report impulse responses of key variables by income groups. First, note in Figure 5 that labour of the poor households increases substantially, while labour of the rich households only increases on impact and then falls. This is more pronounced in the benchmark case, where labour market for the poor is more procyclical. At the same time, consumption of the poor increases markedly, and this is more pronounced in the more procyclical benchmark case. The consumption of the rich is almost unaffected, as they can smooth their consumption by changing their asset holdings. Wages in the benchmark case increase by less, even though the calibrated wage rigidity is the same in both cases shown.

Figure 6 provides an explanation for these observations. When the labour market of the poor is more volatile, firms post relatively more vacancies in this labour market segment during the expansion.[25] With more vacancies labour market tightness in the segment increases, and with it also the job finding probability, causing more employment and more labour income. Households in this labour market segment have a high marginal propensity to consume, which is why their consumption increases strongly. This has aggregate consequences because it increases aggregate demand, which in turn leads to more hiring (again more focussed on the poor labour market segment), leading to further amplification.

More employment in the poor labour market segment, in part, crowds-out employment in the rich labour market segment, which is why we see a decline in labour in that segment. Note that this is not because firms would not want to hire from this segment (tightness

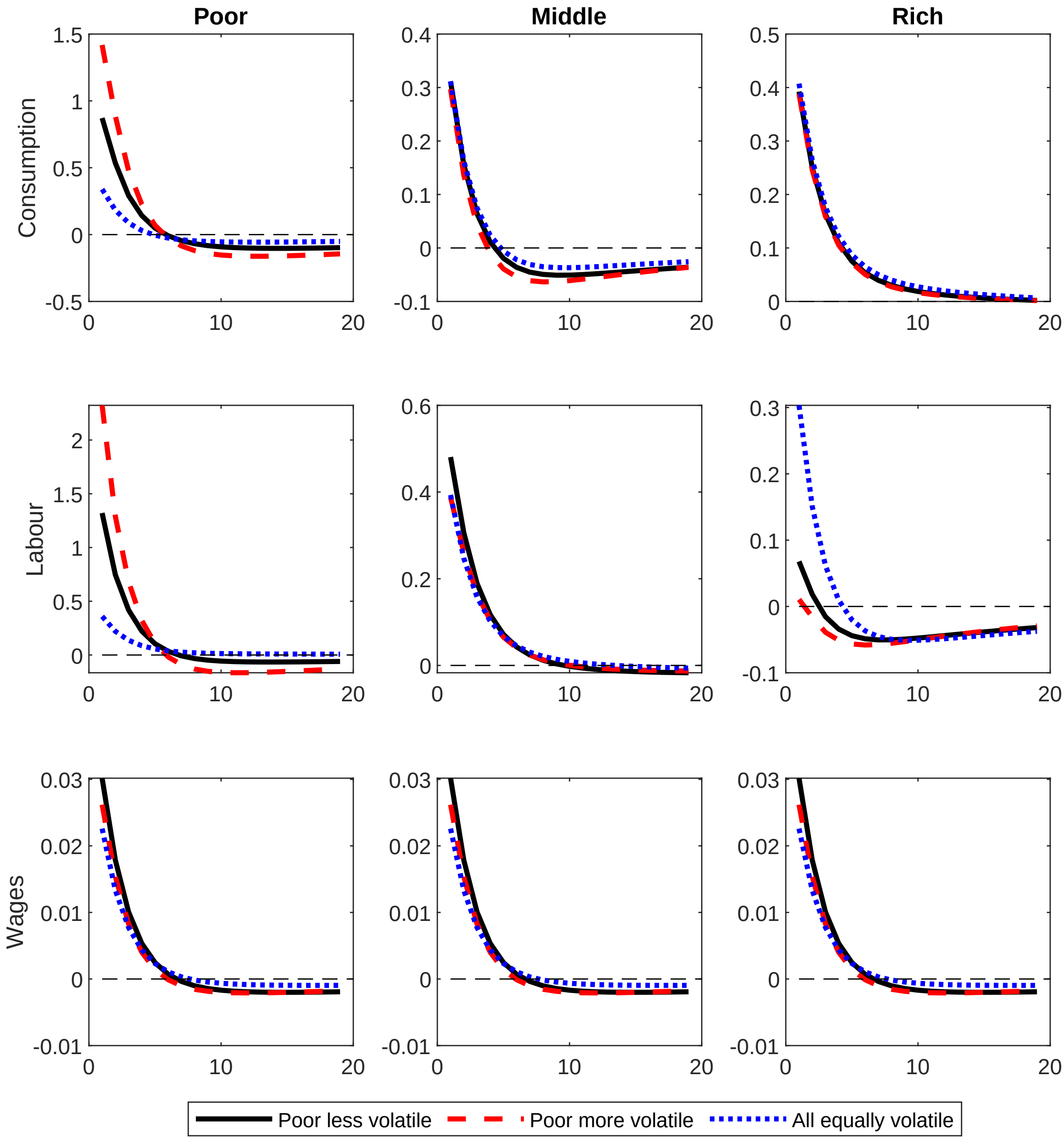
[23]For this specification, entrepreneur’s shares α_{z_h} in Table 6 now read $[0.02, 0.06, 0.11]$. All other parameters are identical to the baseline specification.

[24]In our model, all dividends are given as lump-sum to the rich households, so cyclical properties of dividends do not play an important role.

[25]Recall that in the benchmark case, we calibrated labour firm profits in this segment to be small, in line with Hagedorn and Manovskii (2008), so they increase by more in percentage terms after a positive shock.

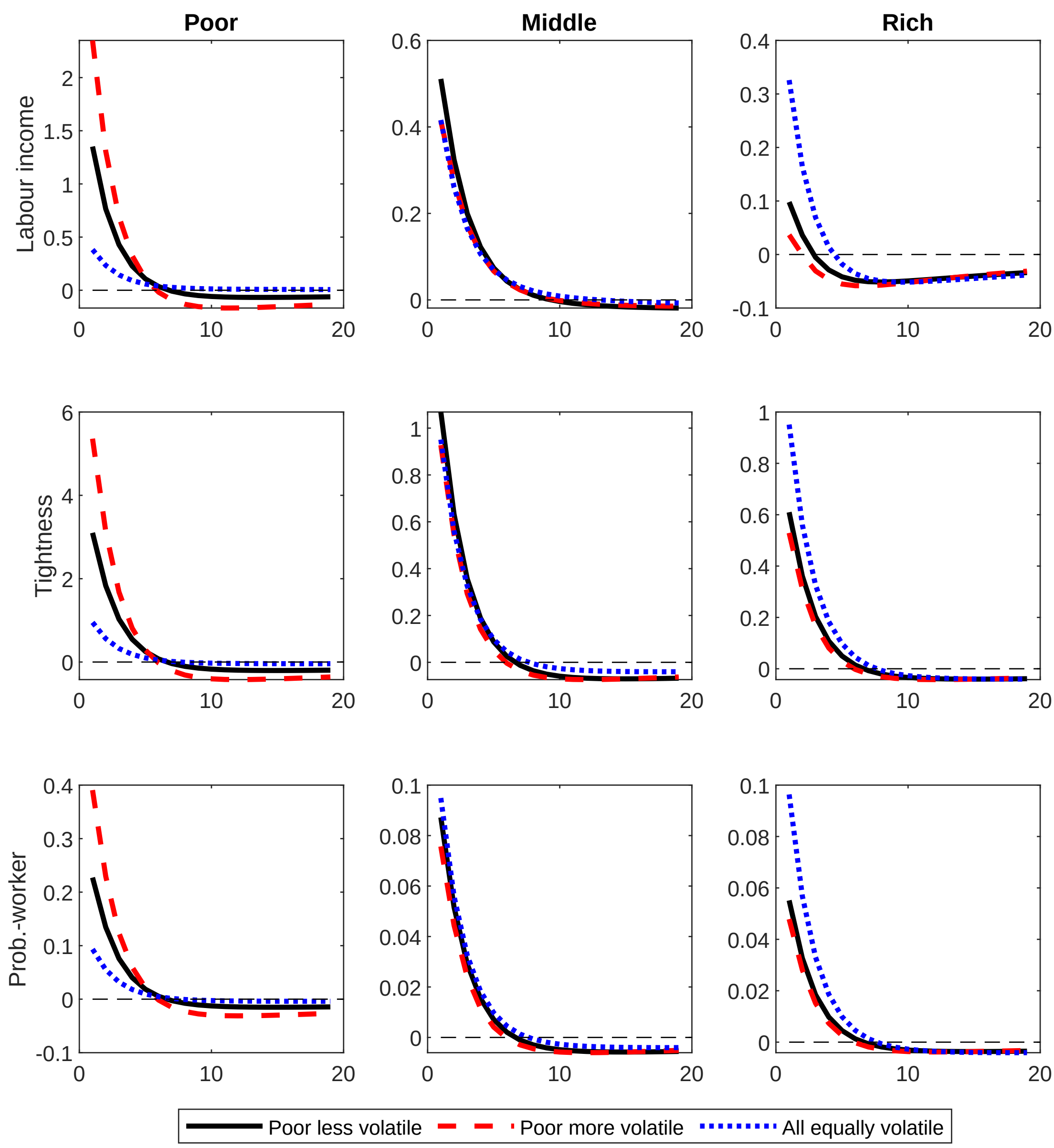
still increases) but because wages do not rise enough to induce the richer households to supply more labour. When labour market segments are similar in terms of their cyclical behaviour, as is the case for Spain-like calibration (shown in dotted blue lines), there is little crowding-out on the labour market by the poor households, which leads to a lower income and consumption response. The same mechanisms apply to the transmission of forward guidance, which is reported in Appendix D.

Figure 5: Effectiveness of monetary policy by groups (1)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 6: Effectiveness of monetary policy by groups (2)



Notes: All variables are reported in percent deviations from the steady state, except probabilities, which are in percentage points. Units on the horizontal axis are quarters.

Note that so far, we have not relied on differences in wage rigidities across labour market segments. This is because we have little hard evidence for European countries that some labour market segments have more rigid wages than others, although this may be the case due to different degrees of unionisation. However, we do have some evidence of differences in wage rigidity in the US, and we investigate these in the next section.

4.2 Calibration for the US

We have little evidence for differences in the wage rigidity for different labour market segments in Europe, but we do have some evidence for the US that wages are more sticky in the labour market for workers with low educational attainment (recall Figure 3). This is important in our model because differences in wage rigidity affect the volatility of a labour firm's surplus and, therefore, vacancy posting. To investigate this issue, we recalibrate the model again, this time to the US (see Table 7), and conduct the following experiments. First, we consider fully flexible wages across all labour market segments. Second, we make all wages equally rigid. Third, we make rigid only wages of the labour market segment for the poor.[26]

Table 7: Matching function and labour firms, US calibration

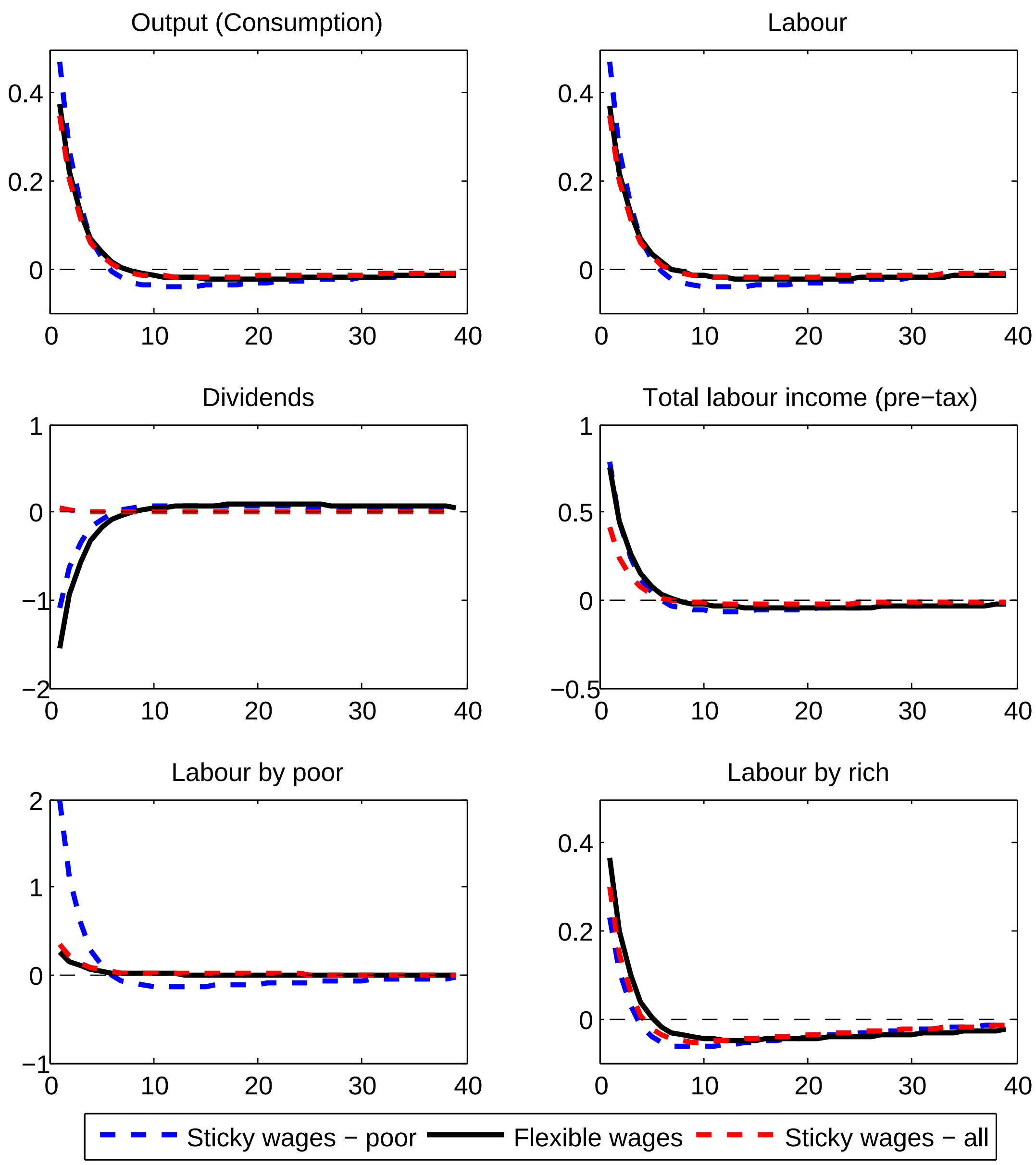
	Parameter	Poor	Middle	Rich
Vacancy posting cost (fraction of lab. end.)	ψ_{z_h}	0.06	0.05	0.04
Matching efficiency	ϕ_{z_h}	0.6	0.6	0.6
Entrepreneur's share	α_{z_h}	0.02	0.05	0.10
Wage rigidity, flexible	ω_R	0	0	0
Wage rigidity, rigid poor	ω_R	0.5	0	0
Wage rigidity, all rigid	ω_R	0.5	0.5	0.5
Job finding probability	p^W	0.60	0.70	0.80

We repeat the simulation of an expansionary and persistent monetary policy shock across the three experiments. First, we consider the flexible-wage case, which is shown in Figures 7, 8 and 9 in full black lines. As one alternative, we assume wages are more rigid in the labour market segment of the less educated (and therefore poorer) households. This setup implies that in response to an expansionary monetary policy shock, labour firms post more vacancies in lower-paying segments with more rigid wages because firm profits in this segment increase by more. Figure 7 shows the result of this experiment in dashed blue lines. Finally, we consider the case where all groups have equally rigid wages, which is shown in red dashed lines. Figures 8 and 9 show the effects by groups of households (each column is one group of households by their labour productivity).

Our main result is that if wages of the poor are rigid, so that they obtain more jobs, then output increases by more than it does when all wages are flexible, and also more than in the case where all wages are equally rigid. The difference is not negligible, given that the strength of the output response on impact when wages of the poor are rigid is about 0.5%, compared to about 0.4% in the flexible-wage and the rigid-wage cases. This is even more so given that the group of poor households is relatively small in the model (25% of the population).

[26]Because of high job finding probabilities in the US and because we use a Cobb-Douglas matching function, it may happen that matching probability exceeds 1. During the computation, we impose the restriction that if this happens, the matching probability is equal to 1.

Figure 7: Effectiveness of monetary policy depending on who gets jobs

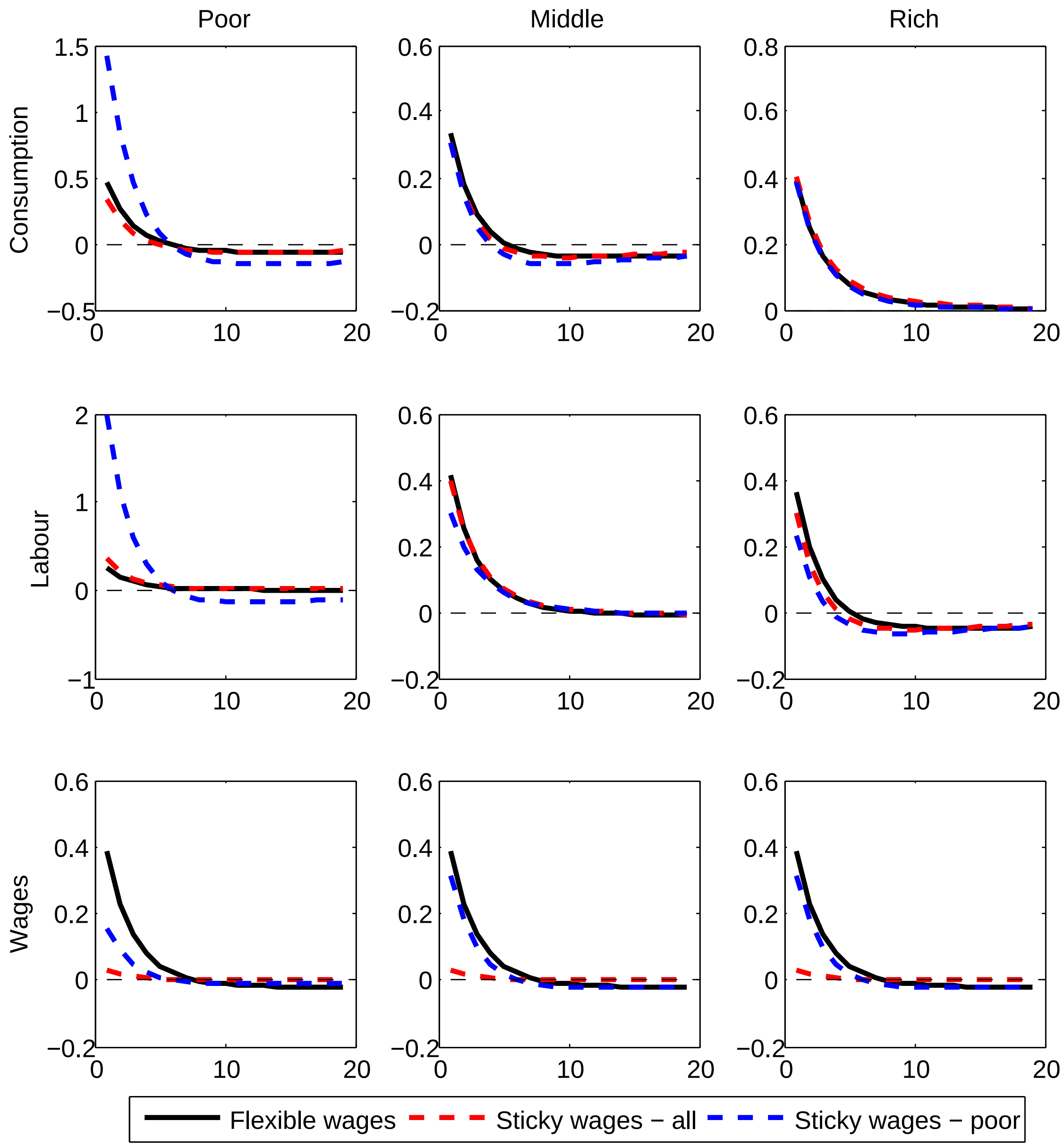


Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

The mechanism that gives rise to this result is similar to the ones discussed above for European countries, just that here the strong increase in labour firm surplus in the poor labour market segment is brought about by both lower entrepreneur's share and higher wage stickiness (for the case shown in dashed blue lines).

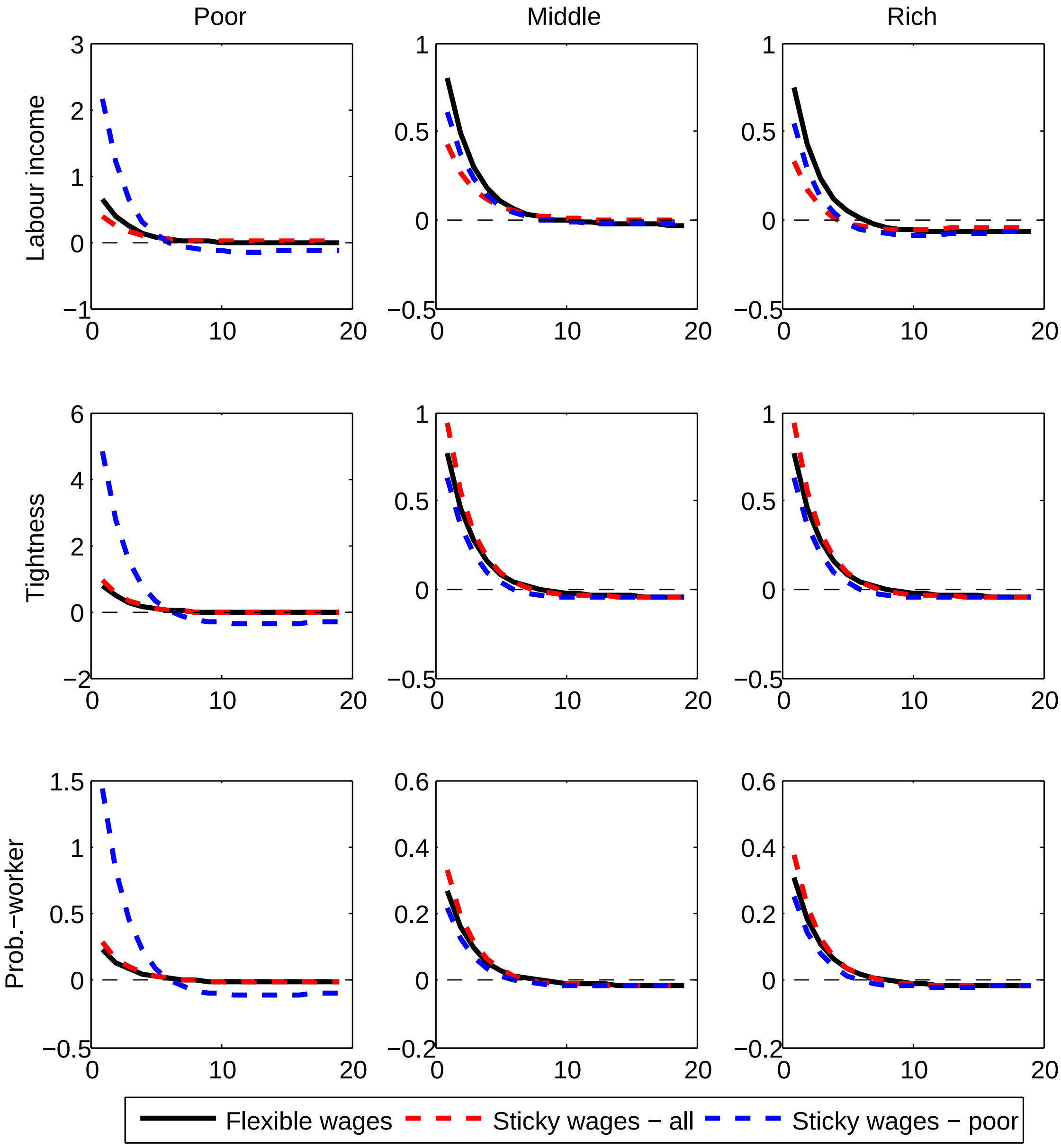
Note that when the wages of the poor are more rigid, the increase in employment is strong enough to compensate for the less income increase due to rigid wages, so the total labour income of the poor increases by more than in the case when wages are flexible. Despite the strong income increase, the reduction in the number of searchers due to the wealth effect is not strong enough to undo the effects of higher labour demand.

Figure 8: Effectiveness of monetary policy by groups (1)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 9: Effectiveness of monetary policy by groups (2)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

5 Conclusion

This paper first documents several empirical characteristics of the job market across educational attainment. We find that in several large European countries labour market at low educational attainment is typically more precarious, with lower job finding rates than those for high educational attainment. Moreover, job finding rates for low educational attainment are typically also more volatile and more procyclical, which indicates higher labour income risk in this segment of the labour market. The situation is similar in the US.

We then construct a stylised incomplete markets model with the search-and-matching framework for labour markets with different educational attainment. We calibrate the model to capture the characteristics that are in line with the empirical findings for Germany, Spain, and the US. We then use the differences to illustrate the transmission channels of standard monetary policy in the model, and extend the analysis to forward guidance.

Our main finding is that the effectiveness of monetary policy on consumption and output is amplified if less educated and hence poorer households tend to obtain relatively more jobs than more educated and richer households after a monetary stimulus. This result is only in part due to the fact that poor households have the largest marginal propensities to consume. There is also a general-equilibrium effect from higher aggregate consumption and output that leads to more labour demand in the less educated labour market segment. When labour markets of the poor are more cyclical, this leads to more hiring in these segments, which amplifies the income and consumption of the poor households and hence aggregate consumption. There may be several reasons that amplify this transmission channel, either higher wage rigidity in the labour market segment for the poor, or lower and hence more volatile profits for hiring a worker from a less skilled labour market segment.

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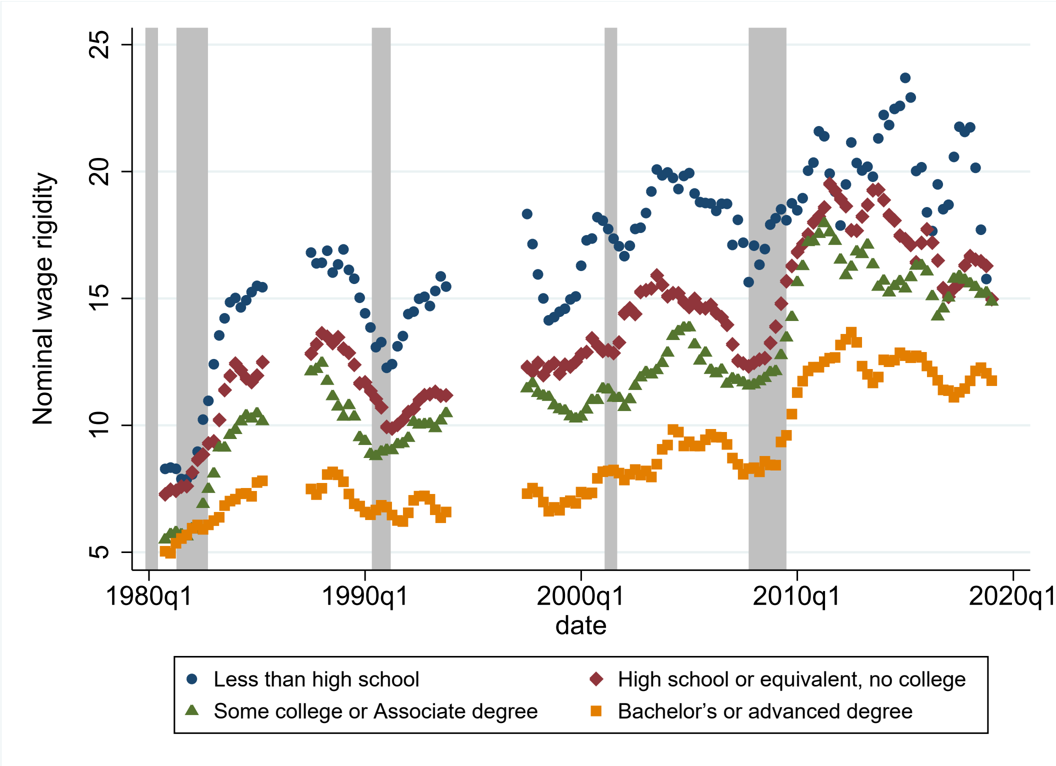
A Appendix Figures

Figure 10: Wage rigidity by educational attainment – Full sample



Notes: Percentage of workers who saw no change in their wage over the past year by educational attainment. Source: https://www.frbsf.org/economic-research/indicators-data/nominal-wage-rigidity/

B Appendix tables

B.1 Monthly outflow hazard rates

Table 8: Monthly outflow hazard rates

		d=3			d=6			d=12		
Country	Sample	L	M	H	L	M	H	L	M	H
Germany	2005Q1-2019Q4	0.15	0.17	0.17	0.15	0.17	0.17	0.14	0.15	0.16
Greece	1998Q1-2020Q4	0.10	0.08	0.09	0.11	0.10	0.10	0.11	0.10	0.10
France	2003Q1-2020Q4	0.12	0.16	0.18	0.12	0.16	0.18	0.12	0.15	0.17
Italy	2001Q1-2020Q4	0.15	0.17	0.21	0.15	0.17	0.20	0.13	0.15	0.16
Spain	1998Q1-2020Q4	0.21	0.21	0.23	0.21	0.21	0.23	0.19	0.19	0.20
UK	2000Q1-2020Q2	0.14	0.19	0.21	0.15	0.19	0.21	0.13	0.17	0.18

Notes: The table reports monthly hazard rates associated with the probability that a worker, who was unemployed at time t, completes the unemployment spell within the next d months. L = Less than primary, primary, and lower secondary education, M = Upper secondary and post-secondary non-tertiary education, and H = Tertiary education. Values are sample averages.

B.2 Alternative measures of a business cycle

Table 9: Worker flows over business cycle

	(1) Net hires	(2) Hires	(3) Separations
NBER recession	-0.013***	-0.015***	-0.004
	(0.001)	(0.002)	(0.003)
Less than high school	0.001***	0.030***	0.029***
	(0.000)	(0.001)	(0.001)
High school or equivalent, no college	-0.001***	0.011***	0.012***
	(0.000)	(0.000)	(0.000)
Some college or Associate degree	-0.000	0.006***	0.006***
	(0.000)	(0.000)	(0.000)
Less than high school × NBER recession	-0.007***	0.002*	0.008***
	(0.001)	(0.001)	(0.001)
High school or equivalent, no college × NBER recession	-0.003***	-0.000	0.003***
	(0.001)	(0.001)	(0.001)
Some college or Associate degree × NBER recession	-0.002**	-0.000	0.001*
	(0.001)	(0.001)	(0.001)
Time FE	X	X	X
Observations	272	276	276
R-squared	0.929	0.971	0.954

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: (Net) hires and separations are rates and are expressed as a share of an average employment within the education group. NBER rec is a dummy variable indicating NBER recessions.

Table 10: Worker flows over the business cycle

	(1) Net hires	(2) Hires	(3) Separations
Less than high school	0.000	0.030***	0.030***
	(0.000)	(0.001)	(0.001)
High school or equivalent, no college	-0.001***	0.011***	0.012***
	(0.000)	(0.000)	(0.000)
Some college or Associate degree	-0.001**	0.006***	0.007***
	(0.000)	(0.000)	(0.000)
Less than high school × UE cycle	-0.007**	-0.006*	0.001
	(0.003)	(0.003)	(0.005)
High school or equivalent, no college × UE cycle	-0.004**	-0.000	0.004
	(0.002)	(0.002)	(0.002)
Some college or Associate degree × UE cycle	-0.002	0.000	0.003
	(0.002)	(0.002)	(0.002)
Time FE	X	X	X
Observations	272	276	276
R-squared	0.895	0.971	0.947

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: (Net) hires and separations are rates and are expressed as a share of an average employment within the education group. UE cycle is the cyclical component of unemployment level within the educational group, obtained by the Hodrick-Prescott Filter using logarithm of seasonally adjusted unemployment level.

B.3 Sensitivity of flows to changes in the GDP

To estimate the sensitivity of changes in (net) hires and separation rates to changes in the GDP across education groups, we estimate the following specification:

$$\Delta Y_{i,t} = \gamma_t + \theta_1 \ educ_i + \theta_2 \ educ_i \times \Delta lnGDP_t + \epsilon_{i,t}, \tag{33}$$

where $\Delta Y_{i,t}$ is the change in either (net) hire or separation rate, $educ_i$ is workers' educational attainment, $\Delta lnGDP_t$ is the change in the logarithm of GDP, γ_t are time dummies to control for common shocks, and $\epsilon_{i,t}$ is the residual term.

Table 11: Sensitivity of worker flows to changes in GDP

	(1) Δ Net hires	(2) Δ Hires	(3) Δ Separations
Less than high school	-0.0007*	-0.0007***	-0.0001
	(0.0003)	(0.0003)	(0.0002)
High school or equivalent, no college	-0.0003	-0.0002	0.0000
	(0.0003)	(0.0002)	(0.0002)
Some college or Associate degree	-0.0002	-0.0001	0.0001
	(0.0003)	(0.0002)	(0.0002)
Less than high school * Δ ln GDP	0.1505***	0.0937**	-0.0542*
	(0.0431)	(0.0370)	(0.0312)
High school or equivalent, no college * Δ ln GDP	0.0767**	0.0429*	-0.0309
	(0.0305)	(0.0227)	(0.0252)
Some college or Associate degree * Δ ln GDP	0.0489	0.0210	-0.0264
	(0.0329)	(0.0279)	(0.0245)
Time FE	X	X	X
Observations	268	272	272
R-squared	0.8720	0.8017	0.8673

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C The remaining model equations

This section describes the remaining model equations. The description closely follows McKay et al. (2016).

Final goods and intermediate goods. Final goods Y_t are produced by bundling intermediate goods $y_{j,t}$, using

$$Y_t = \left(\int_0^1 y_{j,t}^{\frac{1}{\mu}} dj \right)^{\mu} \tag{34}$$

Intermediate goods are produced by a continuum of mass 1 of intermediate goods firms indexed by j according to the following technology:

$$y_{j,t} = n_{j,t}, \tag{35}$$

where $n_{j,t}$ is the amount of labour services hired by the intermediate goods firm j. The final good is produced by a representative competitive firm, but intermediate goods are produced by monopolistically competitive firms. These firms are subject to pricing frictions and can update their prices only with a probability θ per period. The optimisation of the final goods producer implies

$$y_{j,t} = \left(\frac{p_{j,t}}{P_t} \right)^{\frac{\mu}{1-\mu}} Y_t, \tag{36}$$

where $p_{j,t}$ is the price charged by firm j at time t and P_t is the aggregate price level, given by

$$P_t = \left(\int_0^1 p_{j,t}^{\frac{1}{1-\mu}} dj \right)^{1-\mu}. \tag{37}$$

The intermediate producer solves the following problem:

$$\max_{p_t^*, \{y_{j,s}, n_{j,s}\}_{s=t}^{\infty}} \sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} y_{j,s} - W_s n_{j,s} \right), \tag{38}$$

subject to 35 and 36. The solution to this problem is

$$\frac{p_t^*}{P_t} = \frac{\sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} \right)^{\frac{\mu}{1-\mu}} Y_s \mu W_s}{\sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} \right)^{\frac{\mu}{1-\mu}} Y_s}. \tag{39}$$

Government. The government runs a balanced budget, using taxes levied based on (exogenous) labour productivity only to pay interest on otherwise constant bond stock,

$$\frac{B}{1+r_t} + \sum_z \Gamma^z(z) \tau_t \overline{\tau}(z) = B \tag{40}$$

The relation between nominal rate, real rate, and inflation is

$$1 + r_t = \frac{1 + i_t}{1 + \pi_{t+1}}. \tag{41}$$

Equilibrium. In equilibrium, if $\Gamma_t(b, z)$ is the distribution of households asset holdings b over the idiosyncratic state z at time t, that satisfies

$$\Gamma_{t+1}\left(\mathcal{B}, z'\right) = \int_{\{(b,z):g_t(b,z)\in\mathcal{B}\}} Pr\left(z'|z\right) d\Gamma_t(b, z), \tag{42}$$

where $g_t(b, z)$ is the decision rule for household's savings.
Labour supply by households through labour firms has to be equal to labour demand by intermediate goods firms:

$$L_t \equiv \int z_{h,t} l_{h,t}(b, z) d\Gamma_t(b, z), \tag{43}$$

where the aggregation is across household types and their labour supply (note that $l_{h,t}$ depends both on household's wealth and the matching probabilities across labour market segments). Labour market clearing implies

$$L_t = N_t. \tag{44}$$

Aggregate production is

$$N_t \equiv \int n_{j,t} dj = Y_t S_t, \tag{45}$$

where S_t is price dispersion due to nominal rigidities, defined as

$$S_t \equiv \int_0^1 \left(\frac{p_{j,t}}{P_t}\right) dj \tag{46}$$

with the law of motion

$$S_{t+1} = (1-\theta) S_t (1 + \pi_{t+1})^{\frac{-\mu}{1-\mu}} + \theta \left(\frac{p^*_{t+1}}{P_{t+1}}\right)^{\frac{\mu}{1-\mu}}. \tag{47}$$

Inflation can be defined as

$$1 + \pi_t = \left(\frac{1-\theta}{1-\theta\left(\frac{p^*_t}{P_t}\right)^{\frac{1}{1-\mu}}}\right)^{1-\mu}. \tag{48}$$

In addition, labour markets clear, bond markets clear, and goods markets clear (taking into account that dividends are $D_t = Y_t - W_t N_t$)

$$B = \int g_t(b, z) d\Gamma_t(b, z), \tag{49}$$

$$Y_t = C_t. \tag{50}$$

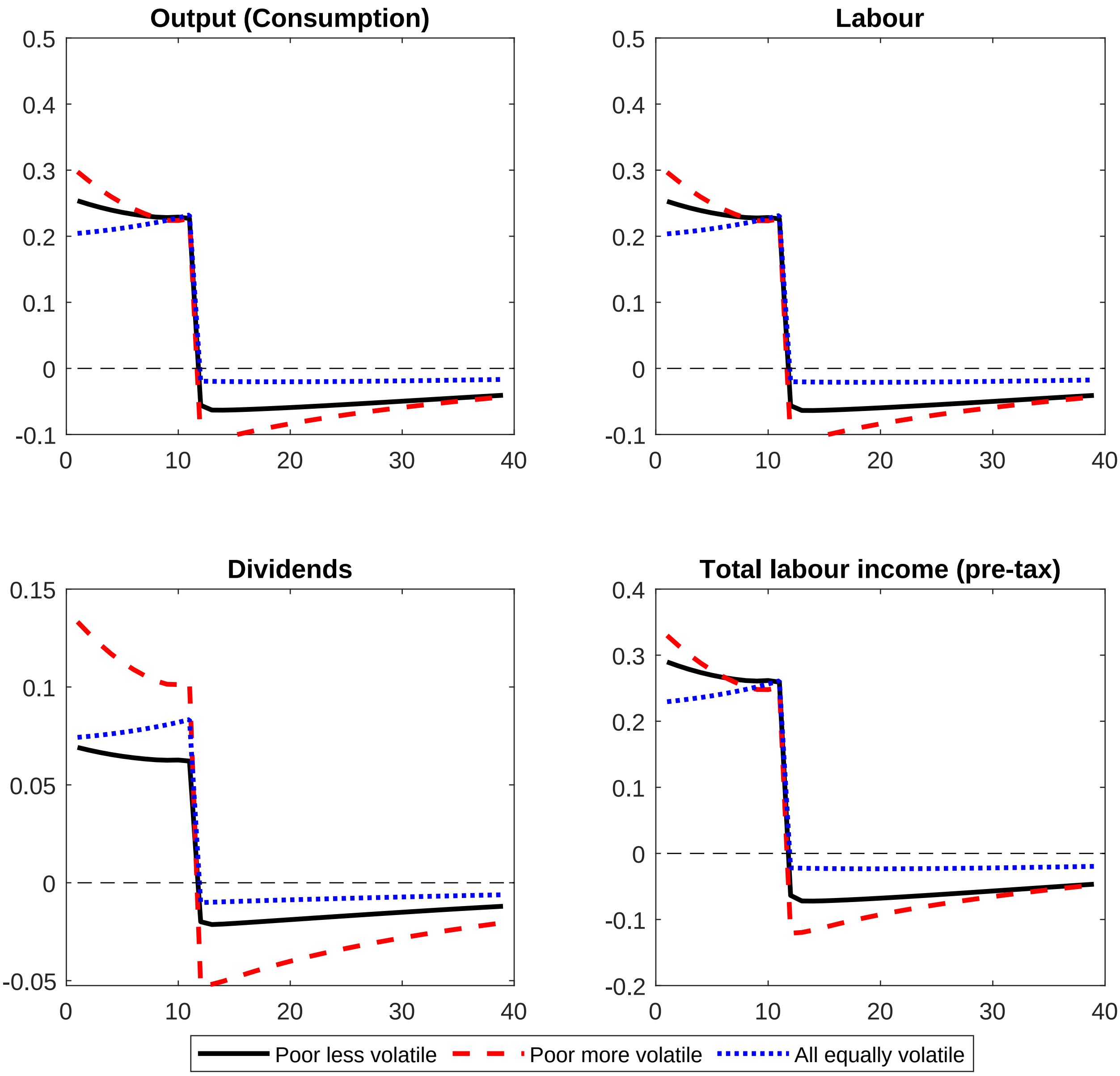
In equilibrium, all decision rules, value functions satisfy all optimality conditions, definitions, and budget constraints.

D Forward guidance and labour market volatility

D.1 European countries

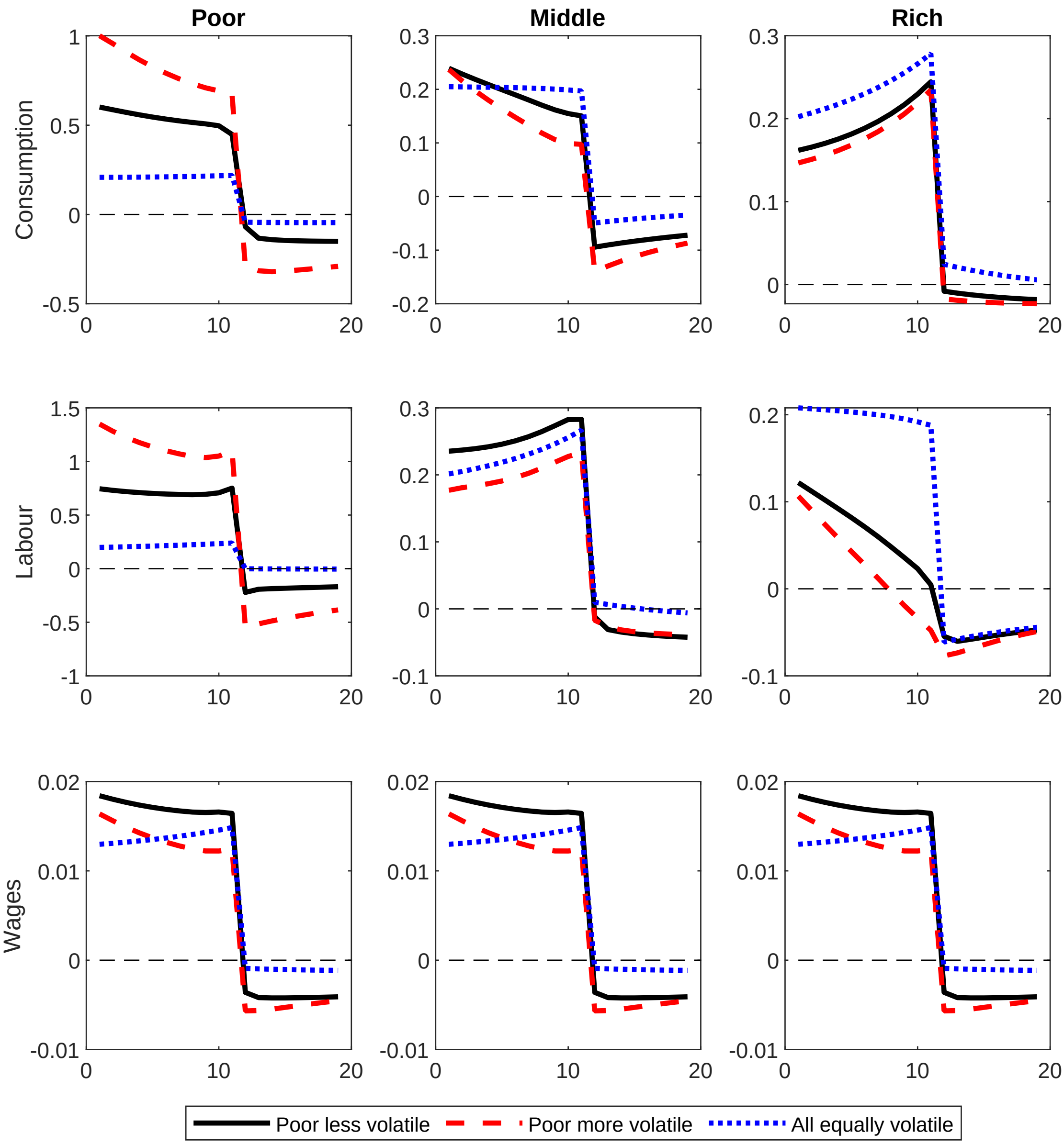
For completeness, this appendix reports the implications of higher volatility on the labour market for the poor on the effectiveness of forward guidance. We simulate forward guidance as a fully credible announcement of a one-time interest rate decrease in period 10. The results are reported in Figures 11 to 13, again for two cases: the red dashed line show our benchmark case, where labour market for the poor is very volatile, and the full black lines show the case where this volatility is smaller (but still higher than in the segments for the middle-income and rich households).

Figure 11: Effectiveness of forward guidance depending on who gets jobs



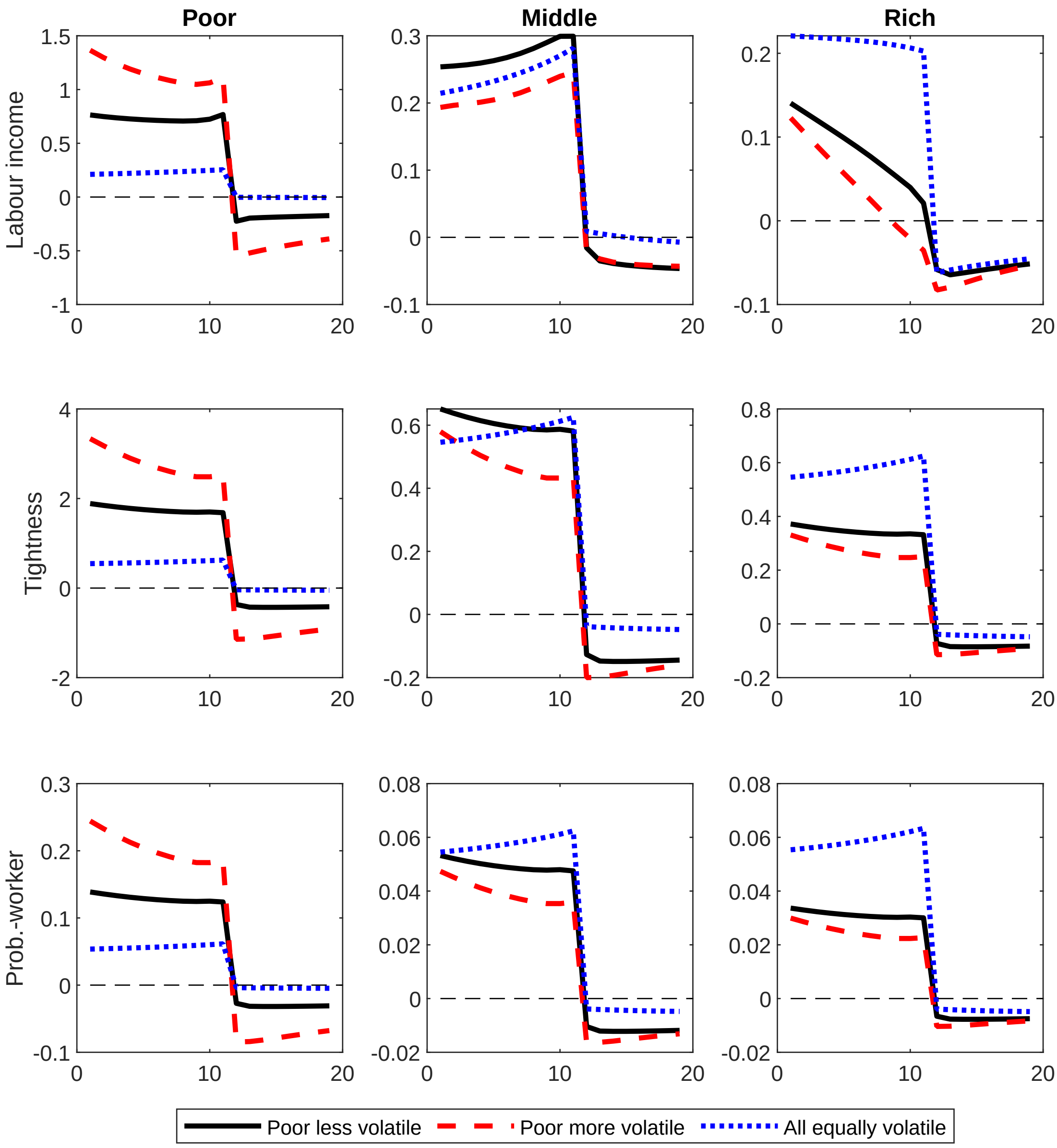
Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 12: Effectiveness of forward guidance by groups (1)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 13: Effectiveness of forward guidance by groups (2)

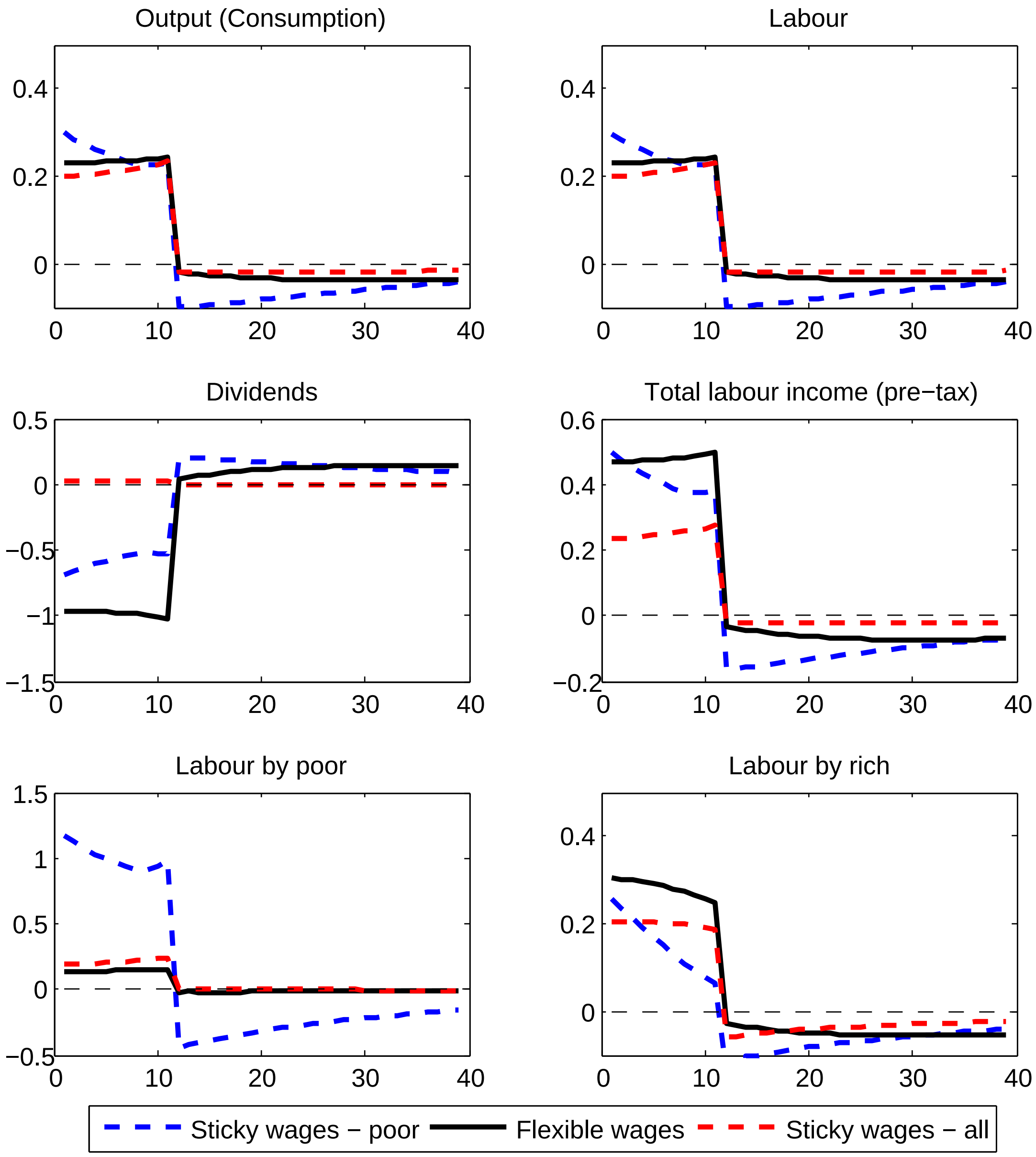


Notes: All variables are reported in percent deviations from the steady state, except probabilities, which are in percentage points. Units on the horizontal axis are quarters.

D.2 Calibration to the US

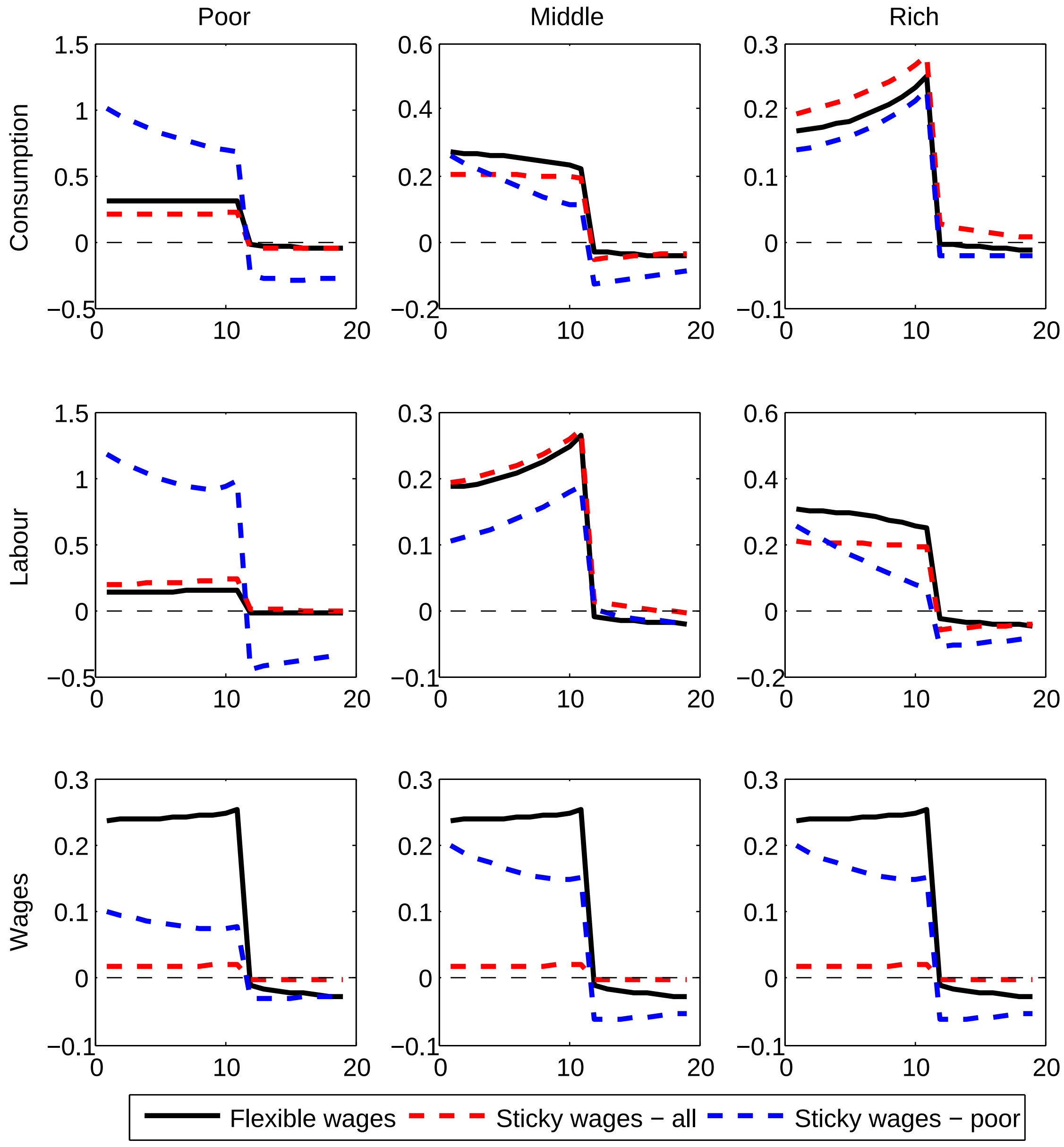
This section reports the implications of different wage stickiness across labour market segments for the effectiveness of forward guidance. Similarly to standard monetary policy in the main text, the effectiveness of forward guidance depends on who obtains jobs. As shown in Figures 14, 15, and 16, the amplification of the forward guidance "puzzle" is mainly driven by the poor obtaining jobs, i.e, the mechanisms at work are similar as for the standard monetary policy shock described above. We obtain the amplification of the strength of the forward guidance only when the poor obtain jobs.

Figure 14: Forward guidance depending on who gets jobs



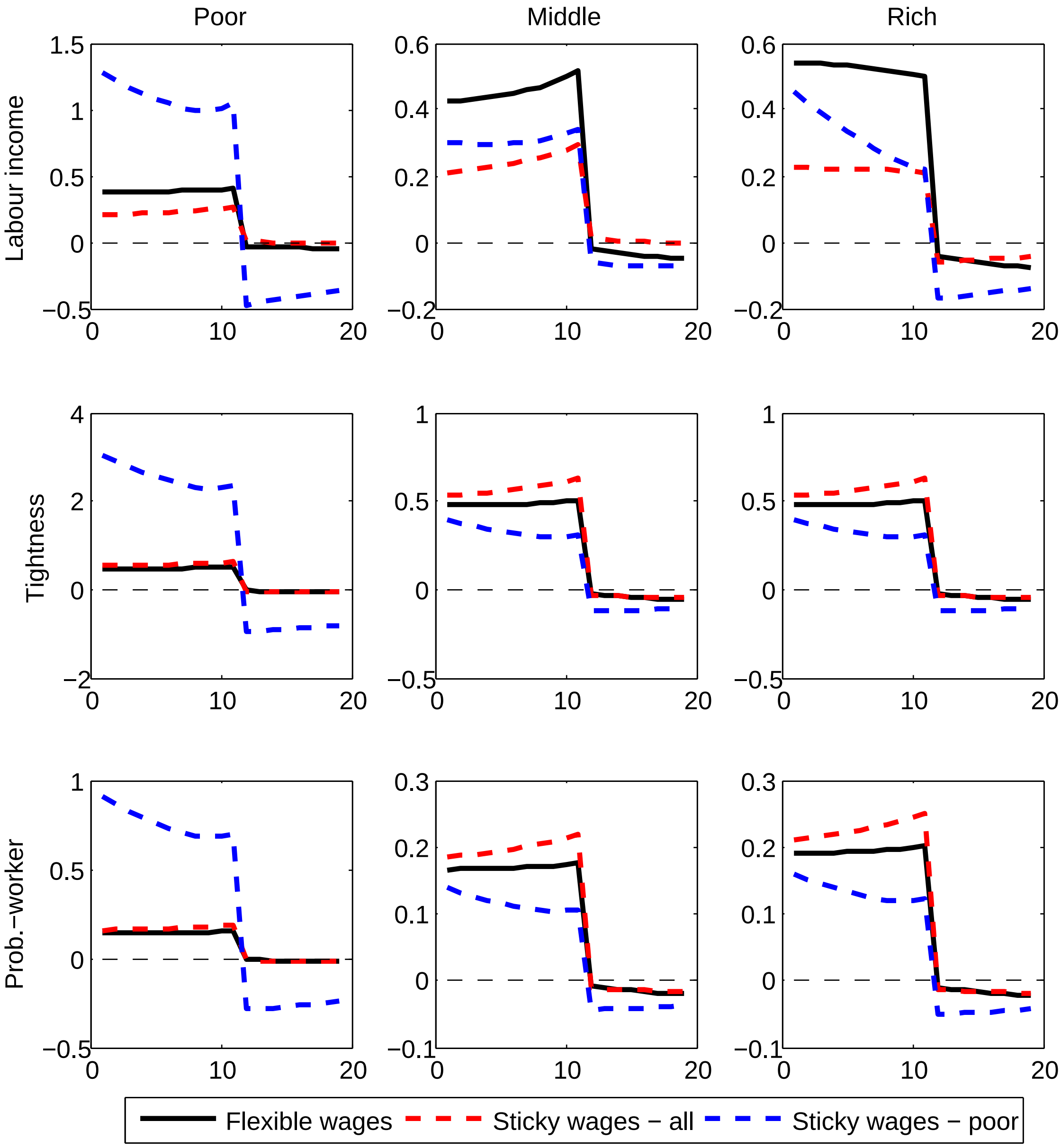
Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 15: Forward guidance, by groups (1)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 16: Forward guidance, by groups (2)



Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.