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

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Non-technical summary

This paper investigates the implications of labour market heterogeneity for monetary policy. Real-world labour market is not homogeneous, and the probability that workers find or lose jobs depends on a number of factors, such as skills, industry etc. While wages are important, the main factors that determine the fluctuations in labour income of a household are the probability to find a job and the probability to lose a job. However, it is not only the levels of these probabilities that matter for labour market outcomes, but also how much they move over the business cycle. To show this, we first report a set of new empirical estimates of job finding and separation rates by educational attainment and their cyclical properties for several European countries. We find that job finding rates for the less educated workers are lower, highly procyclical, and more volatile than for the better educated workers. We also find that separation rates for less educated workers are higher, tend to be more volatile, and often acyclical compared to those for the well-educated workers. There are considerable differences across European countries, but in all cases fluctuations in job finding rates contribute the most to fluctuations in unemployment of the less educated over the business cycle, exceeding 80% in countries like Germany and France. We report similar evidence for the US. In all cases, empirical evidence suggests that workers with low educational attainment face higher employment risk over the business cycle than workers with high educational attainment.

We then build a stylised model with the search and matching (SAM) framework embedded in a heterogeneous-agent New Keynesian (HANK) model that attempts to capture these empirical properties. The labour market in the model consists of a set of separate labour markets corresponding to skill levels, and movements between these markets are rare and can be thought of as persistent changes in the desirability for a particular skill.

Each labour market is different with respect to wage levels, job finding probabilities, and their cyclical properties. On each labour market the job finding probability depends on firms' incentives to create vacancies. These incentives vary with economic conditions, so that the number of vacancies posted by firms and the strength of their response to shocks differs across labour markets. Income fluctuations for households in the same labour market occur because search frictions, combined with wage rigidities, lead to an increased vacancy posting following an expansionary monetary policy shock, which increases job finding rates

and therefore expected labour income *within* each labour market. Because the intensity of vacancy posting differs across labour market segments, the differences *between* labour market segments change over the business cycle and affect the idiosyncratic labour income risk for households. In other words, the income loss/gain due to exogenous shifts from one labour market to another is changing over the business cycle.

We use this framework to investigate the implications of such heterogeneous labour markets for monetary policy. Because workers with lower educational attainment have lower wages and are more likely to be unemployed (in the model and in the data), these workers tend to be poorer than highly-educated workers, whose wages are higher and who are less likely to be unemployed. Because poorer workers also have high marginal propensities to consume from additional income, changes in their employment situation matter more for aggregate consumption and therefore aggregate demand. We show in the model that when less educated (and relatively poor) workers obtain more jobs than other workers after a monetary expansion, which is consistent with empirical evidence for most countries we consider, they also spend a larger proportion of the additional income. This amplifies the increase in aggregate demand after a monetary expansion, which leads to more labour demand, because firms have to hire additional workers in order to produce to meet demand. Because the labour market for workers with lower education is more sensitive to the business cycle, this leads to a relatively stronger increase in employment of these workers, which again leads to a stronger increase in consumption. This feedback loop works as an amplification mechanism that makes monetary policy effects on output 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 for the less educated (and poor) reacts more procyclically than the other labour markets. We show that this can be brought about by two mechanisms that amplify vacancy posting. One such mechanism is a relatively low and, hence, more volatile firm surplus from hiring a worker with a lower educational attainment, and the other is a higher wage rigidity for such workers.

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 labour market outcomes for the less educated, who also tend to be poorer, are substantially more volatile than those for the well-educated, who tend to be richer. We estimate job finding rates and separation rates by educational attainment for several European countries and find that job finding rates are smaller and separation rates larger at lower educational attainment levels. At cyclical frequencies, fluctuations of the job finding rate explain up to 80% of unemployment fluctuations for the less educated. We then construct a stylised HANK model augmented with search and matching and ex-ante heterogeneity in terms of educational attainment. We show that monetary policy has stronger effects when the job market for the less educated and, hence, poorer is more volatile. The reason is that these workers have the most procyclical income coupled with the highest marginal propensity to consume. An expansionary monetary policy shock that increases labour demand disproportionally affects the labour market segment for the less educated, causing a strong increase in consumption. This further amplifies labour demand and increases labour income of the poor even more, amplifying the initial effect. The same mechanism carries over to forward guidance.

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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 issue in the literature has been the so-called earnings heterogeneity channel (Auclert, 2019), which has focussed on the incidence of a particular type of earnings such as interest, dividends, labour income and taxation (Werning (2015), Broer et al. (2019), and Hagedorn et al. (2019)). There was less emphasis on the incidence of labour income itself over the business cycle for different households, even though labour income is typically the most important source of income for the majority of households.

Labour literature tends to find that workers face 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 (2023) 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, because their labour income is lower on average (both due to lower wages and due to more frequent spells of unemployment). 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 Household Finance and Consumption Network (2016)).

Who is rich and who is poor matters in HANK models because households differ in terms of their marginal propensities to consume. 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 (Werning (2015), Acharya and Dogra (2020), Bilbiie (2018)). Moreover, 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 for the US, Guvenen et al. (2017) investigate how individual earnings vary across the wealth distribution, and find that the sensitivity of the workers to the business cycle, the so-called "worker betas", is higher at the bottom and at the top of the earnings distribution. Kramer (2022) finds that the sensitivity is substantially higher at the bottom of the earnings

[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.

distribution (but not at the top) using German data. Moreover, he can attribute this to the fluctuations in the extensive margin rather than to wages. Auclert and Rognlie (2020) 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. A recent example of an approach that provides more micro-foundations for heterogeneous labour market outcomes has been to use capital-skill complementarities (Dolado et al., 2021).

This paper first provides new empirical evidence on job finding and separation rates by educational attainment for several European countries, which is novel and of independent interest. We find that job finding rates for the less educated (and more likely poor) workers are lower, highly procyclical, and more volatile than for the better educated (more likely rich) workers. We also find that separation rates are higher, tend to be more volatile, and often acyclical for less educated workers. There are considerable differences across European countries, with some countries where the labour market seems more homogeneous (with fewer differences by educational attainment) than in others. In all cases, fluctuations in job finding rates contribute most to fluctuations in unemployment of the less educated at cyclical frequencies, with the contribution of job finding rate fluctuations exceeding 80% in countries like Germany and France. We report similar evidence for the US. In all cases, the 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 that attempts to capture the above empirical regularities. 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. Cyclical income fluctuations for households that stay in the same labour market segment occur because search frictions, combined with wage rigidities, lead to an increased vacancy posting following an expansionary shock, which increases job finding rates and therefore expected labour income *within* each labour market segment. Because the intensity of vacancy posting differs across labour market segments, the differences *between* labour market segments change over the business cycle and affect

[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.

the idiosyncratic labour income risk for households (the income loss/gain due to exogenous shifts from one labour market segment to the other).

We use this framework to investigate the implications of such heterogeneous labour markets for monetary policy. We show that if poor workers obtain jobs after a monetary expansion (which is consistent with empirical evidence), they spend a larger proportion of the additional income, because their marginal propensity to consume is higher. This amplifies aggregate demand, which leads to more labour demand from firms that have to produce in order to meet consumption demand. Because the labour market for the poor is more sensitive to the business cycle, this leads to a relatively stronger increase in employment of poorer households, which again leads to a stronger increase in consumption. This works as an amplification mechanism that makes 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 attainment. 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 focusing on the differences between labour market segments and their implications for shock transmission. Compared to Ravn and Sterk (2020) and Ravn and Sterk (2017), we consider the interplay between several labour market segments and allow agents to save. Den Haan et al. (2017) allow agents to save in two assets and solve the model fully globally, but they analyse a unified labour market. Gornemann et al. (2016) do not differentiate between the structure of 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. Kramer (2022) models the transition between labour market segments as endogenous using directed search, while our setting, where educational attainment is predetermined, considers switches between labour markets that require different levels of educational attainment as exogenous (and slow relative to the business cycle frequency). Differently from Dolado et al. (2021), our model generates different labour market outcomes by only relying on labour market search frictions without the need for 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 educated workers can differ markedly over the business cycle. Education level can also serve as a proxy for income and wealth, and the literature has shown that economic policies may affect households across the wealth distribution differently (see, for example, Amberg et al. (2022) or Broer et al. (2022)). This section provides novel empirical evidence for several European countries and the US on who gets and who loses jobs at business cycle frequencies across educational attainment levels, and what are the main driving forces behind it.

Before looking into the driving forces of unemployment fluctuations, it is instructive to examine the variability of unemployment rates across educational attainment levels for selected European countries. Table 1 shows that the unemployment rate at the lowest educational attainment level is much more volatile than the aggregate unemployment rate and the unemployment rates at higher education levels for all countries considered, indicating that those with lower educational attainment are much more exposed to business cycle fluctuations. The remainder of this section examines the underlying forces that drive fluctuations in unemployment rates, focussing on job finding and separation rates and their behaviour at business cycle frequencies.

Table 1: Variability of unemployment rates over business cycles

		Volatility $\sigma(u_i)$				Relative volatility $\sigma(u_i)/\sigma(u)$		
Country	Sample	Agg.	L	M	H	L	M	H
France	2003Q1-2019Q4	0.35	0.57	0.36	0.28	1.60	1.00	0.80
Germany	2005Q1-2019Q4	0.25	0.36	0.28	0.16	1.41	1.11	0.64
Greece	1998Q1-2019Q4	1.39	1.55	1.60	1.00	1.12	1.15	0.72
Ireland	2001Q1-2019Q4	1.07	1.54	1.33	0.60	1.44	1.25	0.56
Italy	2001Q1-2019Q4	0.47	0.61	0.43	0.35	1.31	0.92	0.75
Spain	1998Q1-2019Q4	1.23	1.57	1.23	0.85	1.27	0.99	0.69
UK	2000Q1-2019Q4	0.37	0.61	0.41	0.25	1.65	1.11	0.66

Notes: The table reports standard deviations of cyclical components of unemployment rates u_i, and relative volatilities with respect to the aggregate unemployment rate u, by educational attainment. $Agg.$ = aggregate, L = Less than primary, primary, and lower secondary education, M = Upper secondary and post-secondary non-tertiary education, and H = Tertiary education. We end the sample in Q4 2019 to exclude the COVID-19 period. Cyclical components were obtained using the Hodrick-Prescott filter (smoothing constant of 1600).

2.1 Job finding rates and separation rates by educational attainment in Europe

To estimate job finding rates by educational attainment, we use 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 is based on monthly data).[4]

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 $f_t^{<1}$

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

Following Shimer (2012), we refer to f_t as the job finding rate and to F_t as the corresponding job finding probability. 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 hazard rate as

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

We follow this approach, using quarterly data on unemployment by educational attainment collected by Eurostat, and EU–LFS data on unemployment duration spells, also by educational attainment.[5] We do so for $d \in \{3, 6, 12\}$, and for three levels of educational attainment: (L) Less than primary, primary, and lower secondary education, (M) Upper secondary and post-secondary non-tertiary, and (H) 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,

[4] As pointed out by Elsby et al. (2013), there could be an issue of duration dependence for data at a lower frequency, if the labour market is very fluid, so that job finding rates and separation rates are high. However, they note that this is less of a problem for most Continental European countries, where labour markets tend to be less vibrant than in the US, and for which Elsby et al. (2013) find no evidence for duration dependence.

[5] Data are seasonal, so we first compute 4-quarter moving averages to remove seasonal fluctuations. The advantage of this over seasonal adjustment of each series is that it preserves additivity, i.e., moving averages of unemployed by educational attainment add up to the moving average of total unemployed; moving averages of the employed and unemployed sum to the moving average of the total labour force.

as pointed out by Elsby et al. (2013). Second, the data is quarterly, and we distinguish by educational attainment, which further reduces the sample. This means that for 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 2: Monthly job finding rates

		$f^{<3}$			$f^{<6}$			$f^{<12}$		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	0.043	0.059	0.068	0.044	0.059	0.067	0.042	0.055	0.061
Germany	2005Q1-2019Q4	0.055	0.064	0.063	0.055	0.063	0.064	0.049	0.054	0.057
Greece	1998Q1-2019Q4	0.032	0.026	0.031	0.040	0.033	0.035	0.039	0.035	0.036
Ireland	2001Q1-2019Q4	0.036	0.057	0.070	0.038	0.056	0.066	0.035	0.049	0.055
Italy	2001Q1-2019Q4	0.054	0.063	0.077	0.054	0.063	0.073	0.045	0.052	0.058
Spain	1998Q1-2019Q4	0.081	0.081	0.089	0.080	0.080	0.087	0.068	0.069	0.075
UK	2000Q1-2019Q4	0.049	0.068	0.077	0.052	0.070	0.079	0.047	0.061	0.066

Notes: The table reports monthly job finding rates f_t using (5). 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

Table 2 reports monthly job finding rates based on our estimates that can be compared to those in Elsby et al. (2013).[6] Three main results stand out in these estimates. First, there are considerable differences across countries, with job finding rates ranging from less than 0.03 in Greece to above 0.08 in Spain. Second, the job finding rate rises with educational attainment and is the highest for those with tertiary education and above (H). However, there are exceptions, such as Greece and Spain, where the job finding rate does not increase (or only mildly increases) with the level of educational attainment.[7] Finally, and consistently with Elsby et al. (2013), we find that duration dependence does not seem to play a role - our estimates of levels and volatilities are similar for various durations.

With the estimates of job finding rates f_t, it is possible to back out the corresponding separation rates s_t (and the corresponding separation probability S_t). Shimer (2012) advocates using the following formula, which accounts for the fact that a worker who loses a job can find a new one within the same period:

$$u_{t+1} = \frac{\left(1 - e^{-(f_t+s_t)}\right) s_t}{f_t + s_t} l_t + e^{-(f_t+s_t)} u_t \,, \tag{6}$$

where l_t is labour force and e_t is employment (and $l_t = e_t + u_t$).[8] This equation allows

[6] Table 13 in appendix reports quarterly job finding probabilities $F_t^{<d}$ that we use in Section 3 to calibrate the model.

[7] 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.

[8] Accounting for the possibility that workers can lose and find a job within the period could in principle be

us to solve for the separation rate implicitly. We apply it to each educational attainment level, using our estimates of job finding rates by educational attainment and by duration of unemployment. The results are reported in Table 3.

Table 3: Monthly separation rates

		$s^{<3}$			$s^{<6}$			$s^{<12}$		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	0.007	0.006	0.004	0.007	0.006	0.004	0.007	0.005	0.004
Germany	2005Q1-2019Q4	0.007	0.003	0.002	0.007	0.003	0.002	0.006	0.003	0.001
Greece	1998Q1-2019Q4	0.005	0.006	0.004	0.006	0.007	0.005	0.006	0.007	0.005
Ireland	2001Q1-2019Q4	0.005	0.005	0.003	0.005	0.005	0.003	0.005	0.005	0.003
Italy	2001Q1-2019Q4	0.007	0.006	0.005	0.007	0.006	0.005	0.006	0.005	0.004
Spain	1998Q1-2019Q4	0.020	0.014	0.010	0.020	0.014	0.010	0.018	0.012	0.008
UK	2000Q1-2019Q4	0.005	0.004	0.003	0.005	0.004	0.003	0.005	0.004	0.002

Notes: The table reports monthly separation rates s_t using (6). 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

Separation rates in Table 3 are higher for lower educational attainments than for higher educational attainment levels, except in Greece, where the separation rates are relatively close for all three educational attainment groups. Overall, the evidence from job finding and separation rates is consistent with the notion that the risk of becoming unemployed, and not finding a job quickly once unemployed, is higher for workers with lower educational attainment.[9]

2.1.1 Cyclical properties of job finding and separation rates

Further characteristics that are of interest are the volatility and cyclical behaviour of the estimated job finding and separation rates.

Table 4 reports the standard deviation and correlation of the cyclical components of the estimated job finding rates with the cyclical component of the total unemployment rate.[10] Three characteristics stand out. First, the job finding rates of the least educated (L) tend to be more volatile in some countries (France, Germany, the UK) than job finding rates of those with better education, especially when considering unemployment for each particular educational attainment level (note that the highest education level, H, is quite volatile mainly because of very small samples for this segment, so the results should be interpreted with caution).[11] Second, job finding rates at all educational levels are procyclical (they are negatively

important in our case because of the quarterly data frequency. However, because we find for all countries in our sample that hazard rates f_t and s_t are low (as in Elsby et al. (2013)), this is less of a concern.

[9] In Appendix A.1, we also plot monthly job finding $f_t^{<d}$ and separation rates $s_t^{<d}$ by educational attainment across selected European countries for different unemployment duration spells.

[10] Cyclical components were obtained using the Hodrick-Prescott filter with the smoothing coefficient of 1600, applied to average monthly rates in the quarter, as in Fujita and Ramey (2009).

[11] While we do not emphasise this aspect here, job finding rates for the least educated tend to also be highly

correlated with unemployment). Third, there is considerable heterogeneity across countries regarding the cyclical properties across educational attainment levels. In Germany, the M and H educational levels are almost acyclical; in Italy, L is mildly procyclical, and M and H are more procyclical than L. Similarly, procyclicality tends to increase mildly with educational attainment in Spain, while in Greece, all educational levels are similarly procyclical. In France, Germany, and the UK, lower educational attainment levels tend to be more procyclical.

Table 4: Cyclical properties of job finding rates

		Rel. own vol. $\sigma(f_i)/\sigma(U_i)$			Rel. aggregate vol. $\sigma(f_i)/\sigma(U)$			Corr. with agg. unemployment		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	13.93	11.38	14.19	14.96	11.80	19.01	-0.61	-0.43	-0.56
Germany	2005Q1-2019Q4	16.51	12.58	16.03	15.86	13.99	22.98	-0.46	-0.19	-0.08
Greece	1998Q1-2019Q4	8.08	5.92	9.15	7.75	6.37	9.69	-0.39	-0.42	-0.41
Ireland	2001Q1-2019Q4	9.01	6.96	9.15	7.92	7.88	10.57	-0.30	-0.52	-0.29
Italy	2001Q1-2019Q4	11.38	12.12	16.67	11.83	12.04	19.17	-0.23	-0.41	-0.50
Spain	1998Q1-2019Q4	8.52	10.46	10.84	9.08	9.84	10.84	-0.59	-0.71	-0.80
UK	2000Q1-2019Q4	12.76	12.28	11.21	11.36	13.78	15.40	-0.34	-0.42	-0.26

Notes: The table reports standard deviations of cyclical components of monthly job finding rates relative to the standard deviation of the cyclical component of each group's unemployment U_i, aggregate unemployment U, and correlations of cyclical components of monthly job finding rates with the cyclical component of aggregate 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

The same set of cyclical statistics as for the job finding rates is reported in Table 5 for separation rates. Several results stand out. First, separation rates are less volatile than job finding rates relative to all unemployment measures. Second, separation rates for the lowest educational attainments tend to be much more volatile than those for higher educational attainment levels. Third, in particular for Germany and France and to a lesser degree for the UK, separation rates at the lower educational attainment levels are acyclical.

2.1.2 Contributions of job finding and separation rates to unemployment fluctuations

An important question is which rate, the job finding rate or the separation rate, contributes more to the unemployment rate fluctuations over the business cycle. Following Fujita and Ramey (2009), we decompose unemployment variability into contributions from the job finding and separation rates.[12] Specifically, Shimer (2012) shows that if the job finding and separation rates are constant during a period t, then the corresponding equilibrium unemployment rate can be computed using job finding and separation rates as $u_t^{ss} = s_t/(s_t + f_t)$. If trend

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.

[12]The implicit assumption is that the educational attainment of workers does not change materially at business cycle frequencies.

Table 5: Cyclical properties of separation rates

		Rel. own vol. $\sigma(s_i)/\sigma(U_i)$			Rel. aggregate vol. $\sigma(s_i)/\sigma(U)$			Corr. with agg. unemployment		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	1.02	0.83	0.29	1.10	0.86	0.39	-0.08	0.06	0.26
Germany	2005Q1-2019Q4	1.47	0.74	0.32	1.41	0.83	0.46	0.01	0.65	0.52
Greece	1998Q1-2019Q4	0.71	0.91	0.58	0.68	0.98	0.52	0.41	0.34	0.21
Ireland	2001Q1-2019Q4	0.95	0.79	0.50	0.83	0.89	0.57	0.56	0.58	0.62
Italy	2001Q1-2019Q4	0.65	0.51	0.44	0.67	0.51	0.51	0.66	0.69	0.44
Spain	1998Q1-2019Q4	1.27	0.93	0.50	1.36	0.87	0.50	0.82	0.81	0.81
UK	2000Q1-2019Q4	0.81	0.50	0.28	0.72	0.56	0.38	0.23	0.47	0.66

Notes: The table reports standard deviations of cyclical components of monthly separation rates relative to the standard deviation of the cyclical component of each group's unemployment U_i, aggregate unemployment U, and correlations of cyclical components of monthly separation rates with the cyclical component of aggregate 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

components are denoted by a bar, then the deviations of unemployment from the trend can be written as

$$ln\left(\frac{u_t^{ss}}{\overline{u}_t^{ss}}\right) = (1-\overline{u}_t^{ss})ln\left(\frac{s_t}{\overline{s}_t}\right) - (1-\overline{u}_t^{ss})ln\left(\frac{f_t}{\overline{f}_t}\right) + \varepsilon_t\,, \tag{7}$$

where ε_t is the residual term. The above equation can be more compactly written as

$$du_t^{ss} = du_t^{sr} + du_t^{jfr} + \varepsilon_t\,, \tag{8}$$

where du_t^{sr} and du_t^{jfr} are the contributions of the separation rate and the job finding rate, respectively. The variance of du_t^{ss} is then

$$Var(du_t^{ss}) = Cov(du_t^{ss}, du_t^{sr}) + Cov(du_t^{ss}, du_t^{jfr}) + Cov(du_t^{ss}, \varepsilon_t). \tag{9}$$

This can be used to attribute the share of cyclical variation in unemployment rate that is explained by the cyclical variations of the job finding rate β^{jfr}, the cyclical variation of the separation rate β^{sr}, and the cyclical variation of the residual β^{ε}:

$$\beta^{jfr} = \frac{Cov(du_t^{ss}, du_t^{jfr})}{Var(du_t^{ss})}, \quad \beta^{sr} = \frac{Cov(du_t^{ss}, du_t^{sr})}{Var(du_t^{ss})}, \text{ and } \beta^{\varepsilon} = \frac{Cov(du_t^{ss}, \varepsilon_t)}{Var(du_t^{ss})}. \tag{10}$$

Table 6 reports the estimates of the contributions of the job finding rate and the separation rate to cyclical fluctuations of unemployment rates (note that $\beta^{jfr} + \beta^{sr} + \beta^{\varepsilon} = 1$). The key finding is that in all countries, fluctuations in the job finding rate are the main contributor to cyclical fluctuations in the unemployment rate. Moreover, this is overwhelmingly the case for all countries at the lowest education level, where fluctuations in the job finding rate typi-

cally explain more than half (and often more than 80%) of the fluctuations in unemployment rates, and more than the share explained by the cyclical fluctuations of the separation rate.

Table 6: Contributions to cyclical variation of unemployment

		β^{jfr}			β^{sr}		
Country	Sample	L	M	H	L	M	H
France	2003Q1-2019Q4	0.96	0.69	0.92	0.01	0.32	0.07
Germany	2005Q1-2019Q4	0.87	0.48	0.55	0.09	0.49	0.44
Greece	1998Q1-2019Q4	0.39	0.41	0.40	0.19	0.18	0.05
Ireland	2001Q1-2019Q4	0.46	0.31	0.34	0.30	0.35	0.44
Italy	2001Q1-2019Q4	0.80	0.85	0.86	0.14	0.17	0.10
Spain	1998Q1-2019Q4	0.52	0.60	0.68	0.41	0.35	0.28
UK	2000Q1-2019Q4	0.64	0.64	0.63	0.31	0.33	0.35

Notes: The table reports contributions of the fluctuations of the job finding rate β^{jfr} and of the separation rate β^{sr} to cyclical fluctuations of the unemployment rate. All is 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. β^{jfr} and β^{sr} do not add up to 1 due to the variance contribution of the residual.

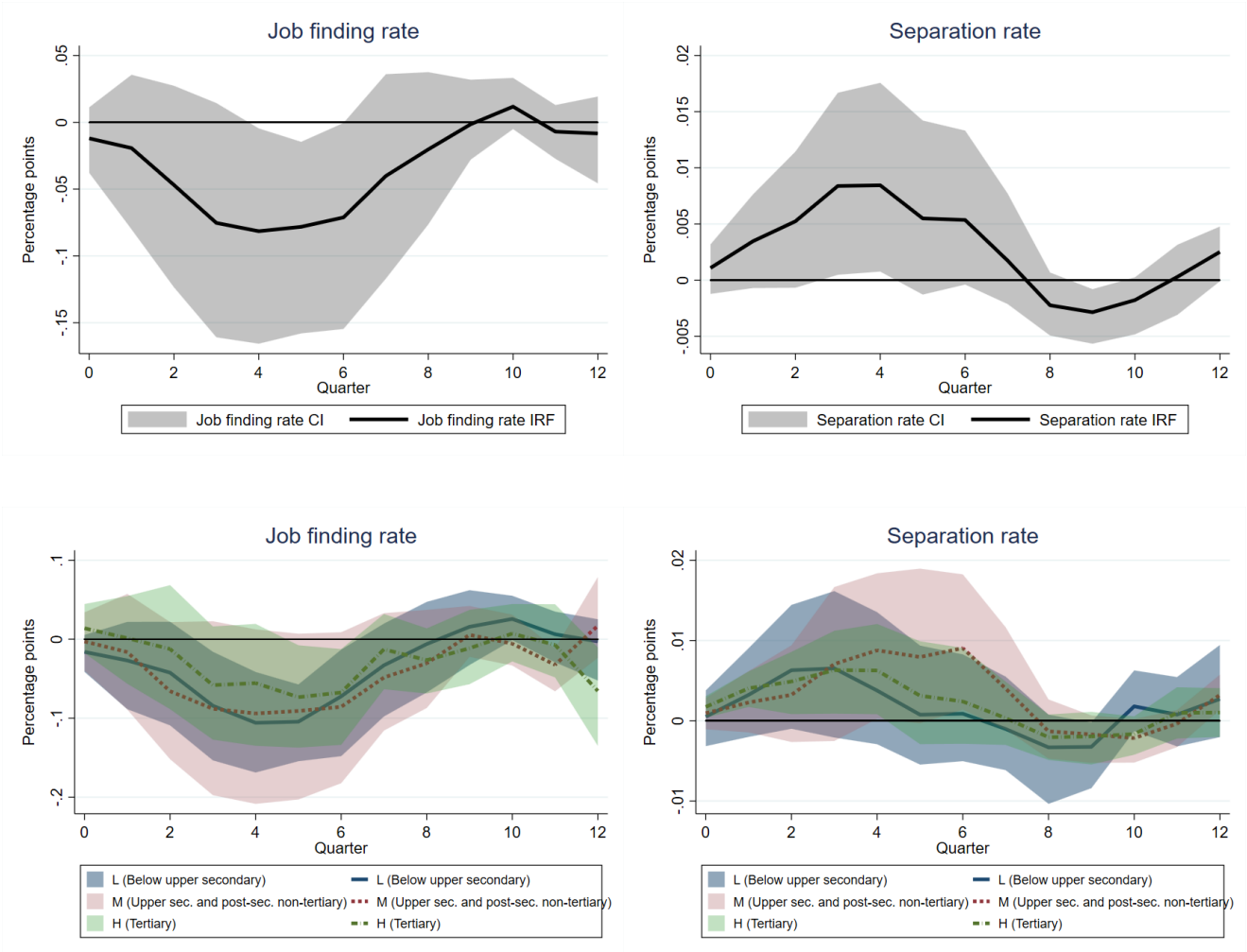
These findings are broadly in line with the empirical evidence for Europe. Slacalek et al. (2020) suggest that, based on *unconditional* estimates, the elasticities of employment responses of hand-to-mouth households, and in particular of poor hand-to-mouth households, tend to be large. While the estimates vary across countries, the sensitivity of employment of poor hand-to-mouth households is at least 1.5-times larger than the aggregate 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. Kramer (2022) studies the procyclicality of earnings growth in Germany and finds that the procyclicality is mostly driven by transitions from nonemployment to employment (i.e. job finding rates), especially at the bottom of the income distribution. Moreover, he finds that individuals at the bottom of the income distribution have lower job finding rates than wealthy individuals and are more exposed to business cycle fluctuations. Both findings are in line with what we find for Germany based on the aggregate data.

2.2 Dynamics conditional on a monetary policy shock

Empirical evidence reported above is unconditional, i.e., driven by all shocks that have affected the economy over the sample period. There is no guarantee that the same properties would also be inherited *conditional* on a particular structural shock, such as the monetary policy shock. Existing empirical evidence conditional on a monetary policy shock (Lenza and Slacalek (2018) and Broer et al. (2022)) suggests that in Europe, the incomes of poor households tend to react more strongly to a monetary policy than the incomes of wealthier households. We investigate whether the stronger reaction to a monetary policy shock is also present in our sample.

To do so, we use a panel local projections approach (Jordà (2005)) for the euro area countries.[13] In particular, we regress job finding and separation rates on identified monetary policy shocks taken from Jarociński and Karadi (2020), and a set of controls.[14]

Figure 1: Responses to a monetary tightening



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands, which are calculated using wild bootstrap cluster robust standard errors (Roodman et al. (2019)). Standard errors are clustered at the country level.

The top two panels in Figure 1 show the responses of the average (not separated by educational attainment) job finding and separation rates to a monetary tightening in the panel of euro area countries.[15] The lower two panels show the same responses to a monetary tightening, but separately by educational attainment levels. All responses have the expected sign (the job finding rate declines and the separation rate increases) and are statistically significant at 90% confidence levels for the average, and for most educational attainment levels.

[13] The sample comprises Austria, France, Germany, Greece, Ireland, Italy, Portugal, and Spain.
[14] See Appendix B.1 for the model specification.
[15] We report the full results for individual countries in Appendix B.2.

Looking at the lower two panels of Figure 1, where job finding rates and separation rates for all educational attainment levels tend to move in unison, one would be tempted to conclude that these responses are not consistent with the empirical evidence cited above that workers at the lower end of the income distribution are more strongly affected by monetary policy shocks. However, this would be a wrong conclusion, because the changes in rates apply to different bases. To see this, consider the standard law of motion for unemployment in equation 1, where the flow out of unemployment is $F_t u_t$. If F_t changes, the outflow from unemployment will depend on the level of unemployment, u_t. Table 7 shows that the unemployment rate for the less educated households in all countries is, except in Greece, by a factor of 2 (for Italy and Spain) or 3 (for all other countries) larger than the unemployment rate for the highly educated. This means that in order to compare the effects of the same change in the job finding rate for those with low and high education on the actual job creation, one would scale this change by a factor of 2 or 3 for the less educated. Therefore, our empirical evidence is consistent with the findings of Lenza and Slacalek (2018) and Broer et al. (2022) and indicates that extensive margin (job finding) is an important factor in driving the dynamics.

An analogous claim could be made for fluctuations in the separation rate. The same change in the separation rate will have less effect on the unemployment of workers with lower educational attainment (relative to those with higher educational attainment), because the proportion of employed workers in this segment is lower.[16]

Table 7: Unemployment rates by educational attainment

		Unemployment rates			
Country	Sample	Aggregate	L	M	H
France	2003Q1-2019Q4	8.97	14.62	8.85	5.56
Germany	2005Q1-2019Q4	6.28	13.33	5.98	2.95
Greece	1998Q1-2019Q4	15.48	15.93	18.01	11.68
Ireland	2001Q1-2019Q4	8.45	14.15	9.59	4.74
Italy	2001Q1-2019Q4	9.50	12.06	8.86	6.05
Spain	1998Q1-2019Q4	16.11	20.97	15.85	10.52
UK	2000Q1-2019Q4	5.77	10.00	5.89	3.14

Notes: The table reports unemployment rates by educational attainment, in percent. $Agg.$ = aggregate, L = Less than primary, primary, and lower secondary education, M = Upper secondary and post-secondary non-tertiary education, and H = Tertiary education. We end the sample in Q4 2019 to exclude the COVID-19 period.

[16]Consistent with equation 1, the law of motion for employed is $n_{t+1} - n_t = F_t u_t - S_t n_t$, where $S_t = 1 - e^{3s_t}$ is the quarterly separation probability. Because n_t in the labour market segment for L is lower than in the other two segments, the same change in S_t as in the other labour market segments will have lower effect on (un)employment.

2.3 Evidence from the US

For the US, compared to European countries, we have more detailed data along several dimensions. First, we have more granular data in terms of educational attainment level. Second, data on new hires includes hires from inactivity. Finally, we also have some evidence that wages at lower educational attainment are more rigid than wages at higher educational attainment levels.[17] The latter will turn out to be important for the quantitative results in the model.

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 2000Q2 and 2017Q3. If not otherwise stated, (net) hires and separations are expressed as a share of employment.

Figures 2a and 2b 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 3 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 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.

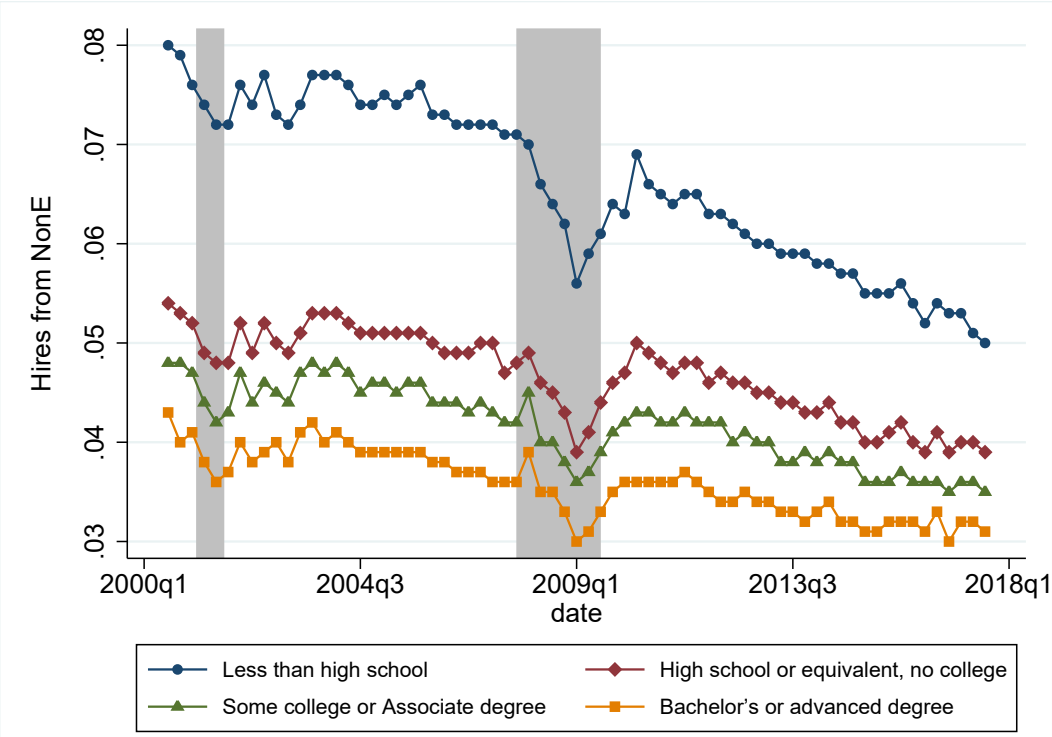
Notably, at the onset of recovery, the net hiring in the groups with the lowest educational attainment is also the one that exhibits the largest jump upwards. Again the pattern is such that the upward jumps are more extreme for the less educated groups, and the magnitudes of the increases decrease with 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 8 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

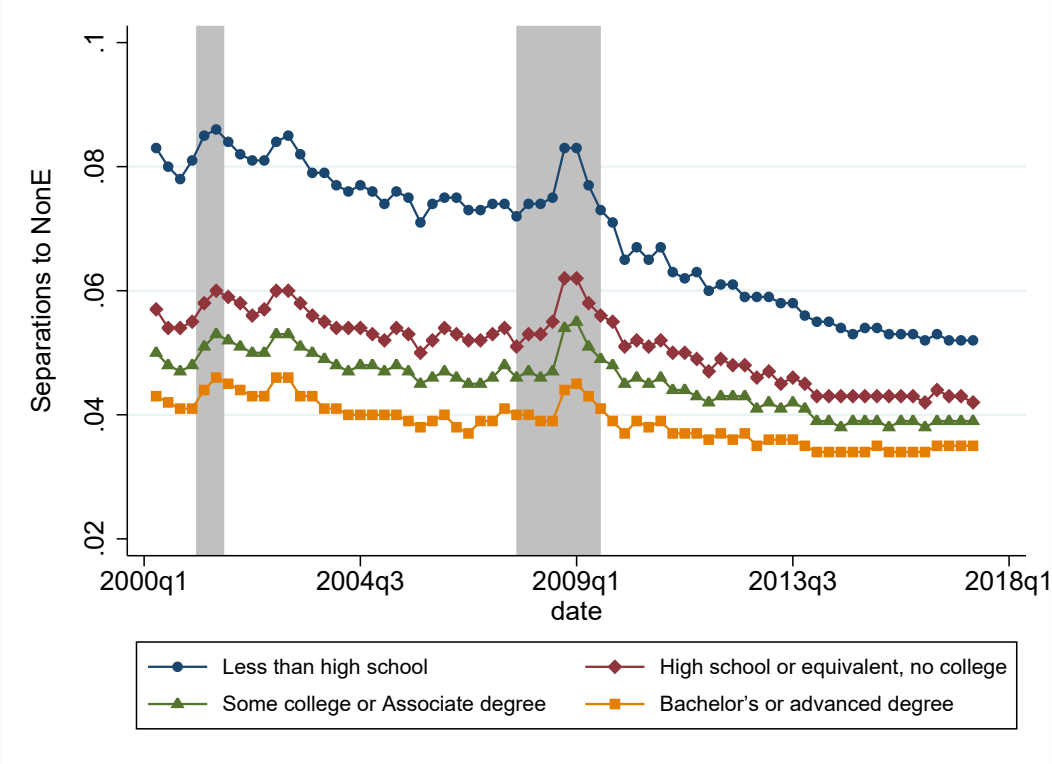
[17] This is the main reason why we report the empirical evidence for the US in a separate subsection.

Figure 2: Hires and Separations to persistent nonemployment

(a) Hires

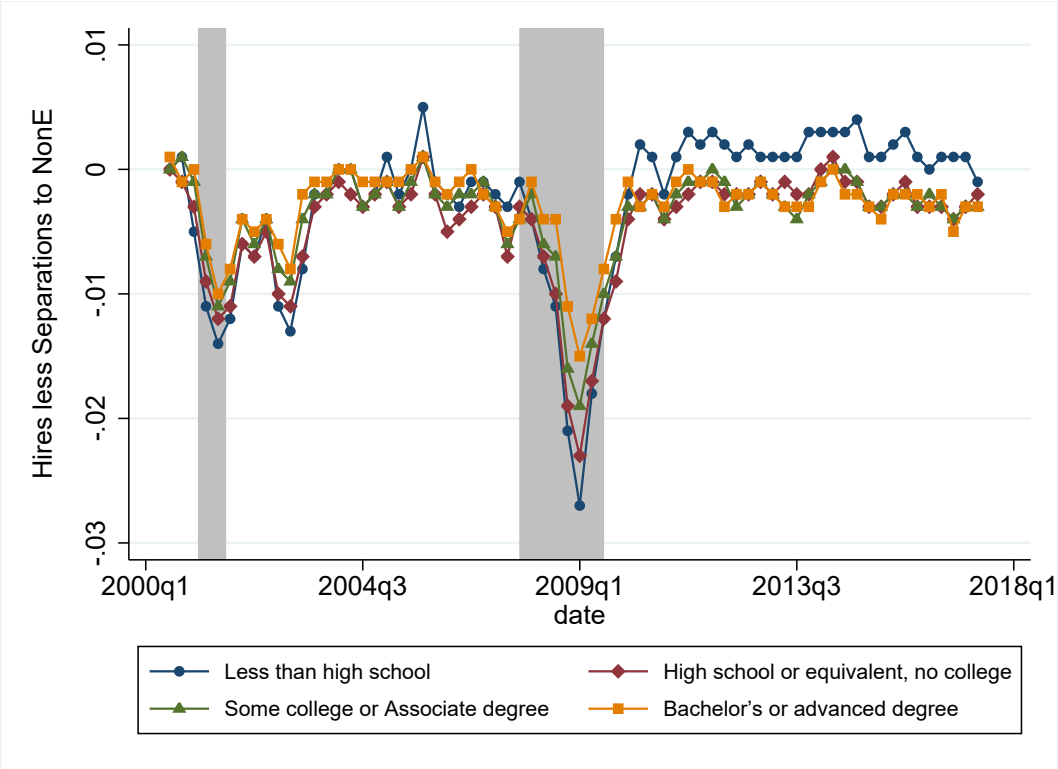


(b) Separations



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.

Figure 3: 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.

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" (expressed as a share of an average employment within the education group) in the last row of Table 8, 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).

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

$$Y_{i,t} = \gamma_t + \beta_1 \, educ_i + \beta_2 \, educ_i \times X_t + \epsilon_{i,t}, \tag{11}$$

where $Y_{i,t}$ is either the (net) hire or separation rate, X_t is the cyclical component of GDP,[18]

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

Table 8: 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.

$educ_i$ 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 in 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.[19]

Table 9: 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.

Table 9 reports the results from estimating Equation 11. 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 the 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

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

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 workers is more cyclically sensitive than for the workers with the highest education.[20] In Appendix Table 19, 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.

2.3.1 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 4 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.[21] 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 levels is Doniger (2023), 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.[22]

3 Model

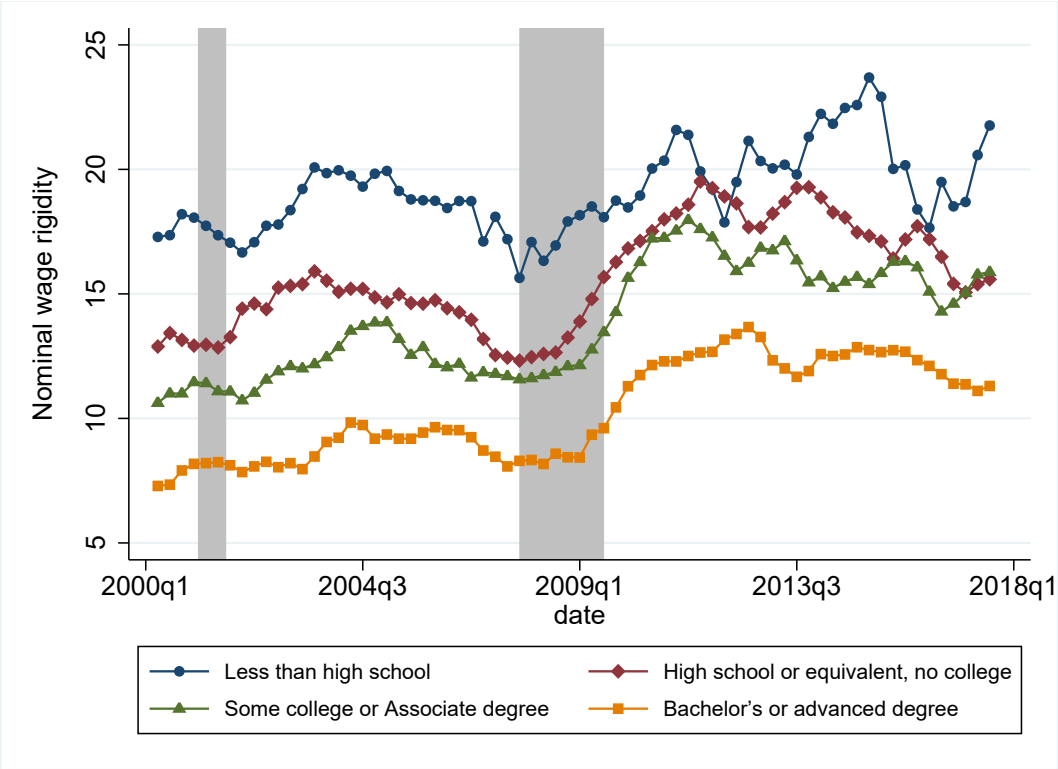
To capture the characteristics of labour market segments described above and to investigate their influence on the effectiveness of monetary policy, we build a small stylised model. The core of the model is the heterogeneous agents New Keynesian model of McKay and Reis (2016) and McKay et al. (2016), which we augment with search frictions on the labour market. To account for the different labour market prospects faced by individual households, we model each labour income level as its own labour market segment.

[20] Interestingly, when we run regression on NBER recession episodes (see Table 17 in Appendix C.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.

[21] See Figure 53 in Appendix C.1 for the full sample.

[22] 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 (2023), they investigate a representative agent setting and do not differentiate across educational attainment.

Figure 4: 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/

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.

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 (educational attainment) 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 continuous variable (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 (and its fluctuations) in each labour market segment by the level and fluctuations of 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 related to the search and matching frictions on the labour market in the model, while the remaining equations are reported in Appendix D. The economy is populated by a continuum of ex-ante identical households who face the following decision problem:

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

subject to

$$c_{h,t} + \frac{b_{h,t+1}}{1+r_t} = b_{h,t} + \overline{b_u} u_{h,t} + w_{h,t} l_{h,t} - \tau_{z_h,t} + \Pi_{z_h,t}, \tag{12}$$

$$s_{h,t} = l_{h,t} + u_{h,t}, \tag{13}$$

$$l_{h,t} = p_{z_h,t}^W s_{h,t}, \tag{14}$$

$$u_{h,t} = (1 - p_{z_h,t}^W) s_{h,t}, \tag{15}$$

and

$$b_{h,t+1} \geq 0. \tag{16}$$

Here, $c_{h,t}$ is consumption of household with the educational attainment 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 $\overline{b_u}$ 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.[23] $P\left(z_{h,t+1}|z_{h,t}\right)$ 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.

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

We assume that all intermediate goods firms are held by an investment fund managed by a risk-neutral manager, who collects profits and distributes them as dividends to households (households cannot trade in equities). Households are allowed to save by holding and trading riskless real 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

$$c_{h,t}{}^{-\gamma} - \lambda_{h,t} = 0, \tag{17}$$

$$-\frac{c_{h,t}{}^{-\gamma}}{1+r_t} + \beta \sum_{z_{h,t+1}} P\left(z_{h,t+1}|z_{h,t}\right) V'_{t+1}(b_{h,t+1}, z_{h,t+1}) = 0, \tag{18}$$

$$-\eta_1 s_{h,t}^{\eta_2} + p_{h,t}^W q_{h,t} - \mu_{h,t} + (1 - p_{h,t}^W)\xi_{h,t} = 0, \tag{19}$$

$$-q_{h,t} + \mu_{h,t} + \lambda_{h,t} w_{h,t} = 0, \tag{20}$$

$$-\xi_{h,t} + \mu_{h,t} + \lambda_{h,t}\overline{b_u} = 0, \tag{21}$$

where $\lambda_{h,t}$ is the multiplier on (12), $\mu_{h,t}$ on (13), $q_{h,t}$ on (14), and $\xi_{h,t}$ on (15).

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

$$c_{h,t}{}^{-\gamma} = \beta(1+r_t) \sum_{z_{h,t+1}} P\left(z_{h,t+1}|z_{h,t}\right) \left(c_{h,t+1}{}^{-\gamma}\right). \tag{22}$$

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:

$$m_{z_h,t} = \phi_{z_h} s_{z_h,t}^{\mu_{z_h}} v_{z_h,t}^{1-\mu_{z_h}}, \tag{23}$$

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

$$p^W_{z_h,t} = \frac{m_{z_h,t}}{s_{z_h,t}} = \phi_{z_h}\left(\frac{v_{z_h,t}}{s_{z_h,t}}\right)^{1-\mu_{z_h}} = \phi_{z_h}\left(\theta_{z_h,t}\right)^{1-\mu_{z_h}}, \tag{24}$$

and the matching probability for the firm, $p^F_{z_h,t}$, is

$$p^F_{z_h,t} = \frac{m_{z_h,t}}{v_{z_h,t}} = \phi_{z_h}\left(\frac{v_{z_h,t}}{s_{z_h,t}}\right)^{-\mu_{z_h}} = \phi_{z_h}\left(\theta_{z_h,t}\right)^{-\mu_{z_h}}. \tag{25}$$

Households' labour supply. Households send workers to search until the cost of searching (measured in monetary terms) is equal to the expected earnings from searching. Rearranging (17), (19), (20) and (21) delivers

$$\frac{\eta_1(l_{h,t}+u_{h,t})^{\eta_2}}{c_{h,t}^{-\gamma}} = p^W_{h,t}w_{h,t} + (1-p^W_{h,t})\overline{b_u}, \tag{26}$$

where $(l_{h,t}+u_{h,t}) \equiv s_{h,t}$ 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, $p^W_{z_h,t}$ is a fraction of workers who find a job and earn real wage $w_{z_h,t}$, and $(1-p^W_{z_h,t})$ is a fraction of workers who do not find a job, but receive unemployment benefits $\overline{b_u}$. Condition 26 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.[24]

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.[25] 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 of these differences, transition from one labour market segment to the other implies a different gain or loss of income, depending on the state of the business cycle.

Labour firms. We assume that each productivity segment of the labour market is populated by a continuum of 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. Each labour firm employs one worker. The value function of the labour firm is

[24] Equation (26) also nests standard labour supply model; if $p^W_{z_h,t} = 1$, so that everyone finds a job (implying $u_{h,t} = 0$), and $\overline{b_u} = 0$, it reduces to the standard labour supply condition.

[25] 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.

$$J_{z_h,t} = \omega_t z_{h,t} - w_{z_h,t}, \tag{27}$$

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

$$\psi_{z_h} = p^F_{z_h,t} J_{z_h,t}\,, \tag{28}$$

where ψ_{z_h} is the per-period vacancy posting cost in the labour market segment with productivity z_h. In equilibrium, the labour firm's optimality condition states that the per-period cost of posting a vacancy 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 wage determination. 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 (which is the revenue received by the labour firm),

$$w_{z_h,t} = (1 - \alpha_{z_h})\omega_t z_{h,t}\,. \tag{29}$$

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.

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.[26] We allow wage rigidity to differ across labour market segments. The rigid wage is then

$$w_{z_h,t} = [(1 - \omega_R)(1 - \alpha_{z_h})\omega_t + \omega_R(1 - \alpha_{z_h})\overline{\omega}]z_{h,t}\,, \tag{30}$$

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

Relation to Nash bargaining. Here we show that our flexible wage rule is just a particular case of the standard Nash bargaining. With Nash bargaining, the wage is the outcome of bargaining between workers and firms regarding the split of the total surplus generated by a successful match. The solution to the Nash bargaining problem is

$$\chi_{z_h} J_{z_h,t} = (1 - \chi_{z_h})(W^E_{z_h,t} - W^N_{z_h,t}), \tag{31}$$

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

where $\chi_{z_h} \in (0,1)$, is the bargaining power of the worker that can be labour-market-segment-specific,[27] $J_{z_h,t}$ is the value of a job for a firm, and $W^E_{z_h,t}$, $W^{UI}_{z_h,t}$ are the value functions of being employed and unemployed. The value functions for a firm and a worker are

$$J_{z_h,t} = \omega_t z_{h,t} - w_{z_h,t}, \tag{32}$$

$$W^E_{z_h,t} = w_{z_h,t} - \eta_1 \frac{(l_{h,t} + u_{h,t})^{\eta_2}}{c^{-\gamma}_{h,t}}, \tag{33}$$

$$W^{UI}_{z_h,t} = \overline{b_u} - \eta_1 \frac{(l_{h,t} + u_{h,t})^{\eta_2}}{c^{-\gamma}_{h,t}}. \tag{34}$$

To get the wage equation, one substitutes (32), (33), and (34) into (31) yielding

$$w_{z_h,t} = \chi_{z_h}(\omega_t z_{h,t} - \overline{b_u}) + \overline{b_u}, \tag{35}$$

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 $\overline{b_u} = 0$, so that there are no unemployment benefits, and define $\chi_{z_h} \equiv (1 - \alpha_{z_h})$, we get exactly (29).

Finally, in order to see how the wage depends on the labour market developments, we substitute (28) and (25), together with (33), and (34) into (31) to obtain

$$w_{z_h,t} = \frac{\chi_{z_h}}{1 - \chi_{z_h}} \left(\frac{\psi_{z_h}}{\phi_{z_h}} (\theta_{z_h,t})^{\mu_{z_h}} \right) + \overline{b_u}, \tag{36}$$

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 probabilities 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 10.

Idiosyncratic risk of transiting from one labour market segment to the other is calibrated using the transition matrix from McKay et al. (2016) who use the persistent component of

[27] 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 would prevent them from posting any vacancies.

Table 10: 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

wage process from Floden and Lindé (2001), approximated using a 3-state Markov process with the transition matrix P:

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

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 11. 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, and since we do not have good data on the differences in the wage rigidity by educational attainment levels, we assume that the degree of wage rigidity is equal across all labour market segments.[28] We investigate the implications of this assumption when we recalibrate the model to US data.

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. The model is quarterly, and we report quarterly probabilities corresponding to the monthly rates from Section 2 in Table 13 in the appendix. Because the job finding probability 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 more volatile and much more procyclical for the low-educated (see Table 15 in the appendix). To do so, we follow the idea in Hagedorn and Manovskii (2008), who propose to solve the puzzle of low volatility of labour market variables in the standard search-and-matching model (Shimer,

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

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.

Table 11: Matching function and labour firms

	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

While modelled on Germany, this calibration is meant to represent the typical case found in the labour data also for other European countries, such as France. We refer to this calibration as "Poor more volatile". 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 15 in the appendix). To illustrate the difference this makes, we also report simulations for the recalibrated model, where labour market segments are similar in terms of their volatilities. We do this by matching job finding probabilities 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. We refer to this calibration as "All equally volatile". Finally, as a counterfactual, we also simulate a calibration where we still keep the volatility of the labour market outcomes of the less educated higher than that for the highly-educated, but we make the difference less pronounced. We refer to this case as "Poor less volatile".

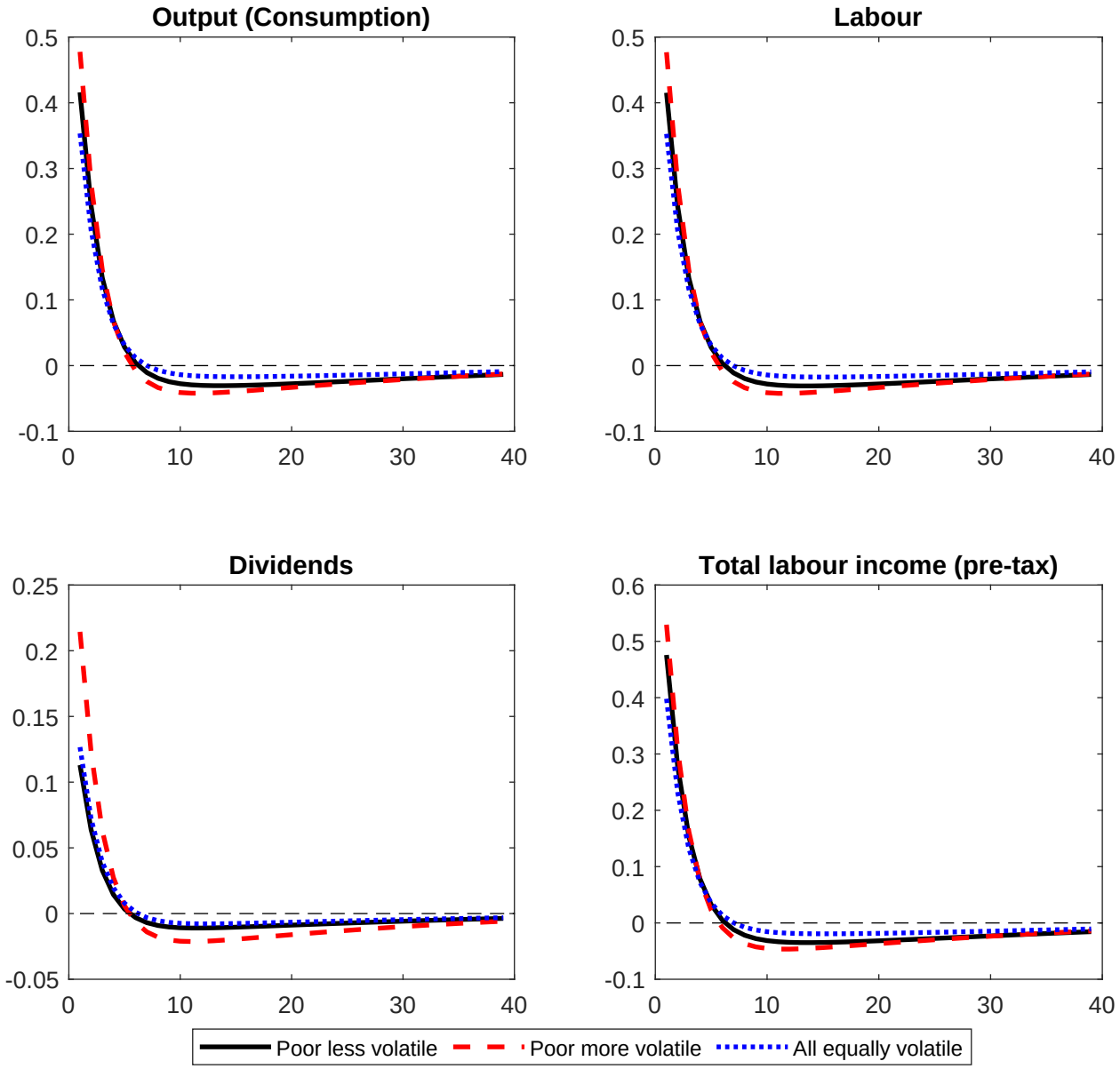
4 Results

4.1 Calibration for European countries

We first simulate a standard monetary policy shock, where the central bank temporarily lowers the real interest rate by half a percentage point.[29] The results are reported in Figures 5 to 7.

[29]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 use a persistence of 0.6 for the AR(1) process governing the shock.

Figure 5: 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.

Figure 5 reports results for the aggregates. The red dashed line represents our benchmark calibration in Table 11, where the labour market segment for the less educated 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 outcomes for the less educated are only half as volatile as the benchmark case (but still more volatile than the other two labour market segments).[30] 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 where the volatility of labour market outcomes is

[30]For this specification, entrepreneur's shares α_{z_h} in Table 11 now read $[0.02, 0.06, 0.11]$.

similar across all labour market segments, which would correspond to countries like Spain (shown as 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. The initial output response is, for instance, 17% higher for the red dashed line compared to the full black line, and this is similar for aggregate labour and labour income responses. The difference in the magnitude of responses is even larger when compared to the symmetric case. Dividends are procyclical due to sticky wages.[31]

To understand the mechanism behind these results, it is instructive to look at the disaggregated quantities. Figures 6 and 7 report impulse responses of the main variables of interest by labour market segments. First, note in Figure 6 that labour of the poor households increases substantially in the benchmark case with the labour market outcomes of the poor more volatile, while labour of the rich households only increases on impact and then falls. This becomes less pronounced if we make the labour market for the poor less procyclical. At the same time, consumption of the poor increases markedly in the benchmark case and follows the pattern of the labour responses if we reduce the volatility in the labour market segment for the poor. Consumption of the rich is almost unaffected by the labour market situation, as they can smooth their consumption by changing their asset holdings.[32] Wages respond symmetrically across all labour market segments, but with the different magnitude for each case considered, because they are determined by the aggregate labour demand and labour supply (recall that the calibrated wage rigidity is the same in all cases shown).

Figure 7 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. This is because labour firm profits in this segment are small, in line with Hagedorn and Manovskii (2008), so they increase by more in percentage terms after a positive shock whenever there is some wage rigidity. 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 for the poor. Households in this labour market segment have a high marginal propensity to consume, which is why their consumption increases strongly. Despite the fact that this labour market segment is small and that consumption of households in this segment is also small, the increase in consumption is sufficient to increase aggregate demand, which in turn leads to more labour demand and again more hiring from the poor labour market segment, leading to further amplification.

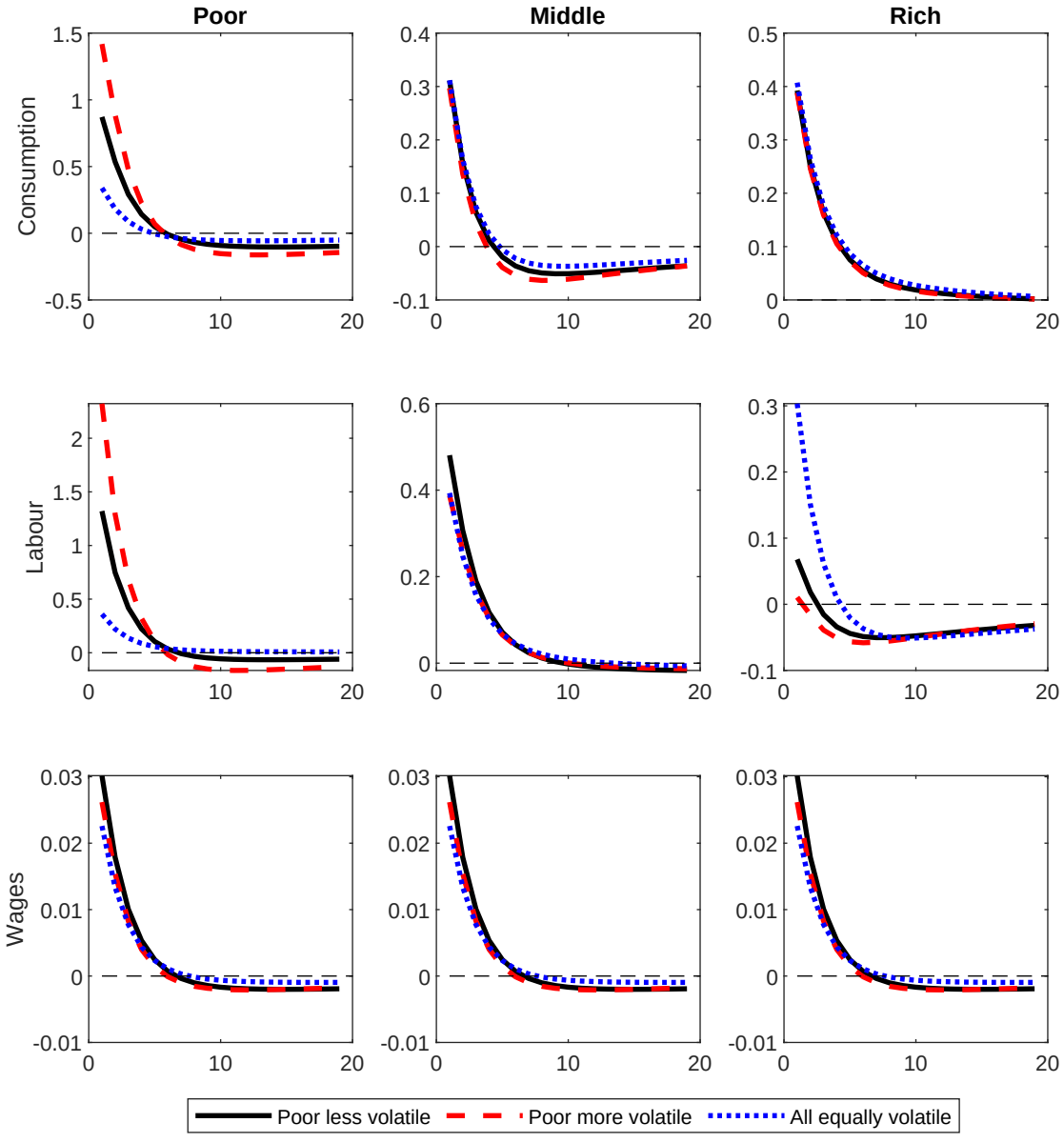
More employment in the poor labour market segment, in part crowds-out employment in the middle and rich labour market segment, which is why we see a decline in labour in that

[31] In our model, all dividends are given as lump-sum to the rich households, who can smooth consumption, so that cyclical properties of dividends do not play an important role. Note that because dividend income is also procyclical, it matters less if we distribute it equally. This is in contrast to McKay et al. (2016), where households that receive a substantial proportion of their income in the form of countercyclical dividends can even see their total income fall after a monetary expansion.

[32] Middle households increase their consumption the least, because they have a relatively less savings and non-negligible propensity to save, which is whay they decide to save some of their additional income.

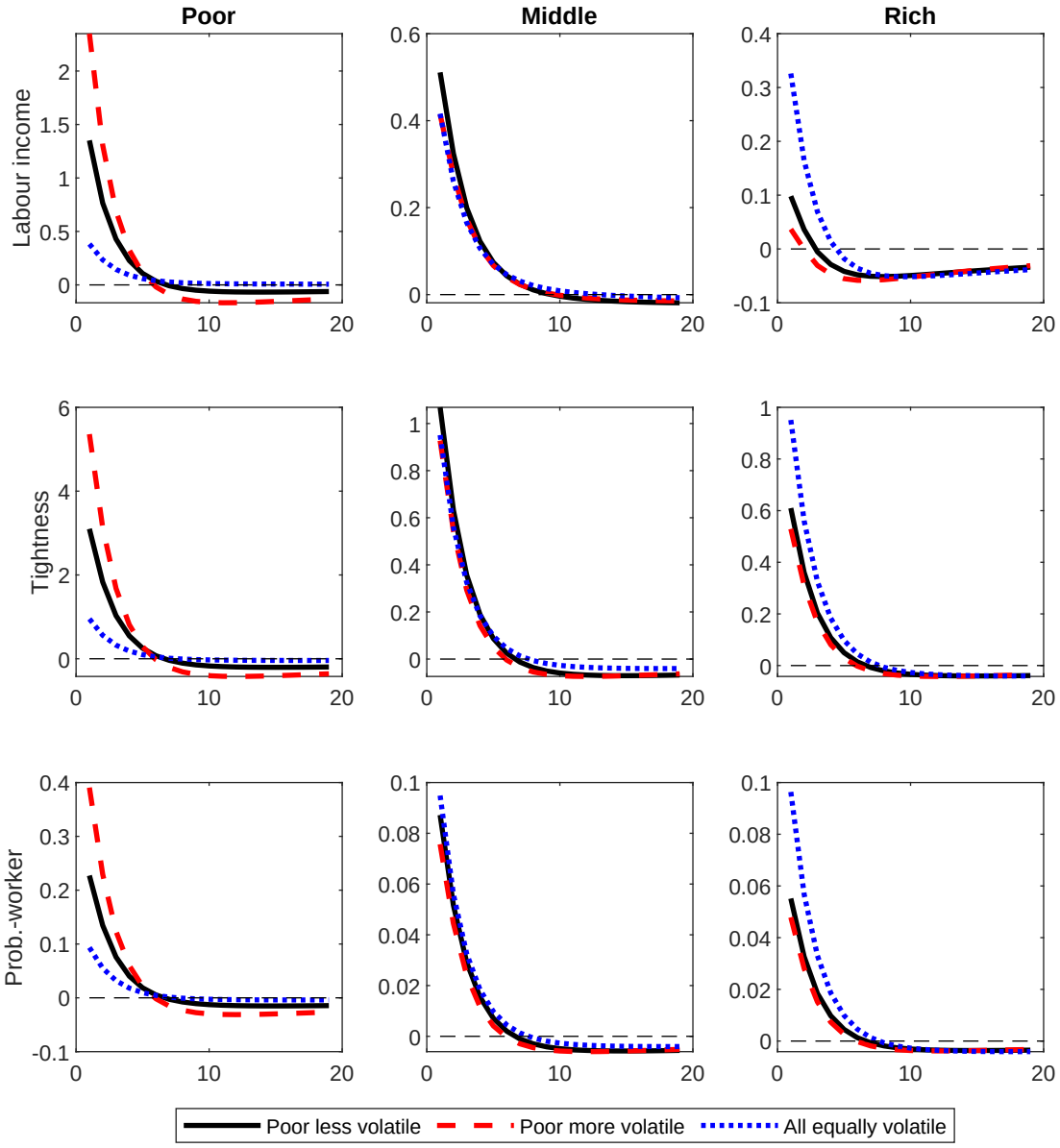
segment for the benchmark case. Note that this is not because firms would not want to hire from this segment (tightness still increases) but because wages and the matching probability in this segment do not rise enough to induce the richer households to supply more labour. When labour market segments are similar in terms of their cyclical behaviour, as is the case for Spain-like calibration (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, reported in Appendix E.

Figure 6: 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 7: Effectiveness of monetary policy by groups (2)



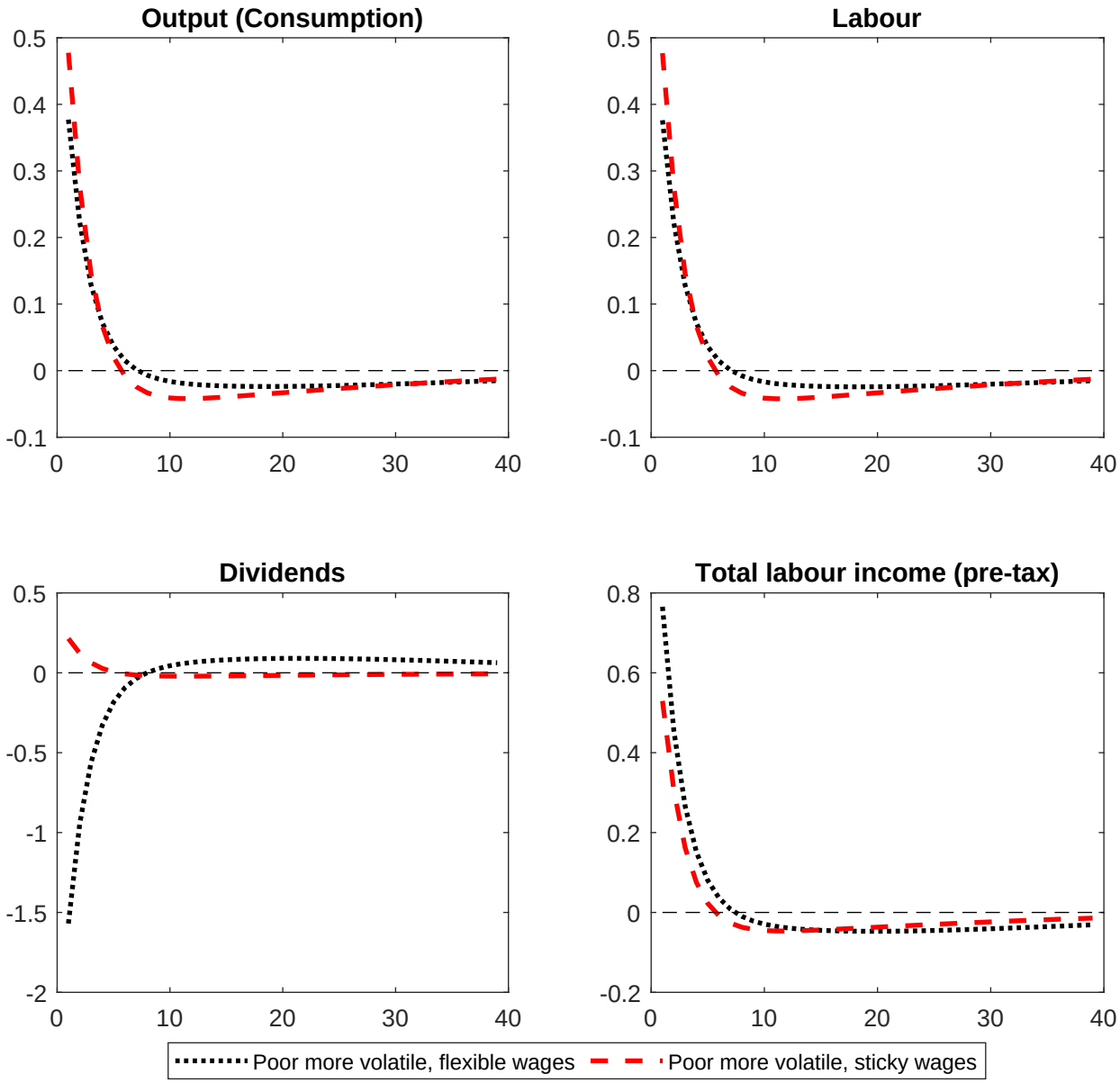
Notes: All variables are reported in percent deviations from the steady state, except probabilities, which are in percentage points. Units on the horizontal axis are quarters.

4.1.1 The role of wage rigidity

The results shown above are, in addition to the friction due to market incompleteness, driven by the interaction of two frictions, wage rigidities and search frictions. This subsection explains the role of wage rigidity in generating the amplification after a monetary expansion. To do so, we re-run the monetary policy shock in calibration to Germany, but this time with fully flexible wages. The aggregate results are reported in Figure 8, and the results for groups by educational attainment in Figures 9 to 10. The red dashed line shows the benchmark results reported above, while the dotted black line shows the case with fully flexible wages.

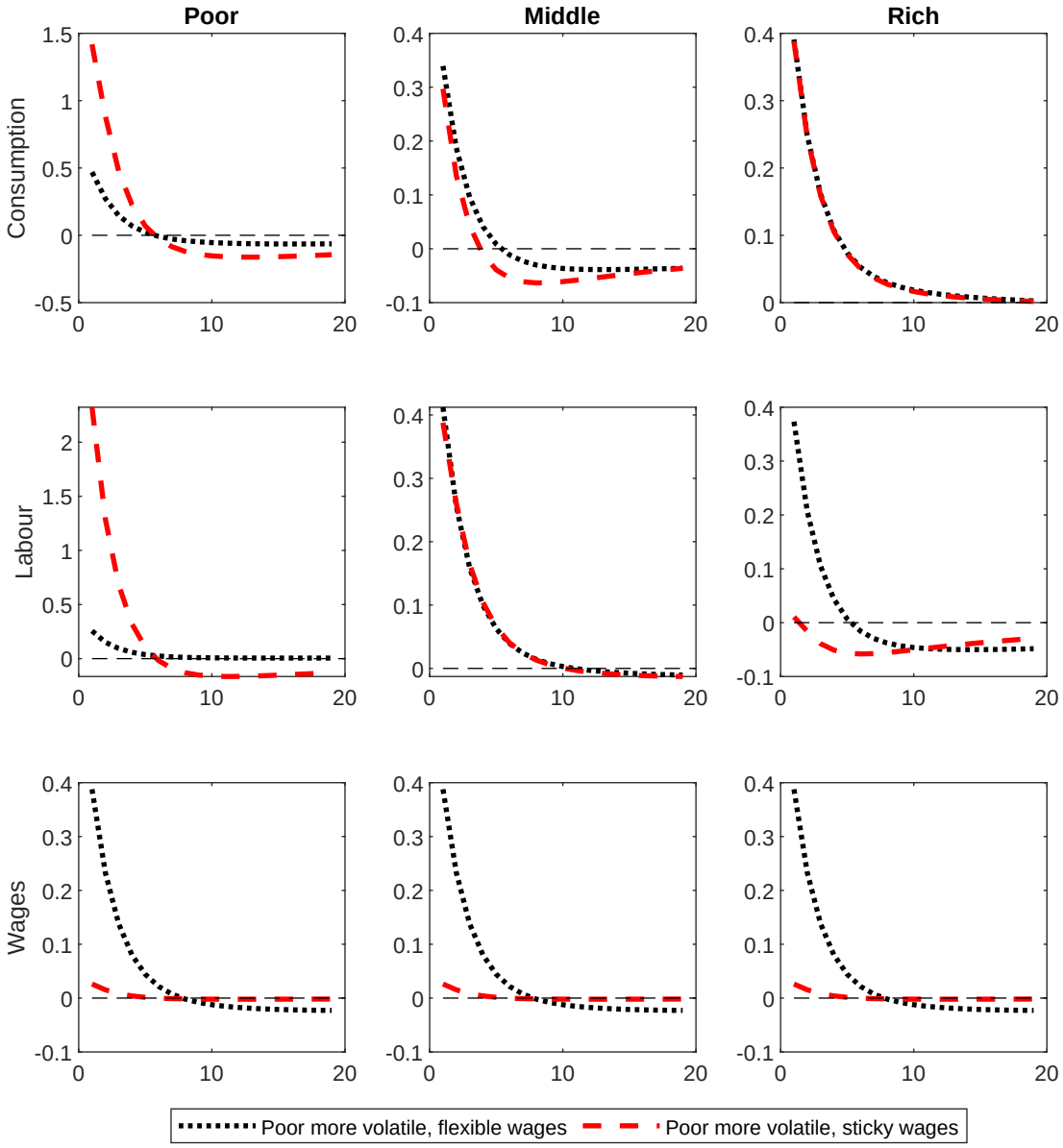
If we first turn to Figure 8, we see that after a monetary expansion, the aggregate labour income increases by more when wages are fully flexible, but aggregate output and labour increase by less, and dividends fall (note that the latter is a standard result in New Keynesian models with sticky prices and flexible wages).

Figure 8: The role of wage rigidity - aggregate



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

Figure 9: The role of wage rigidity by groups (1)



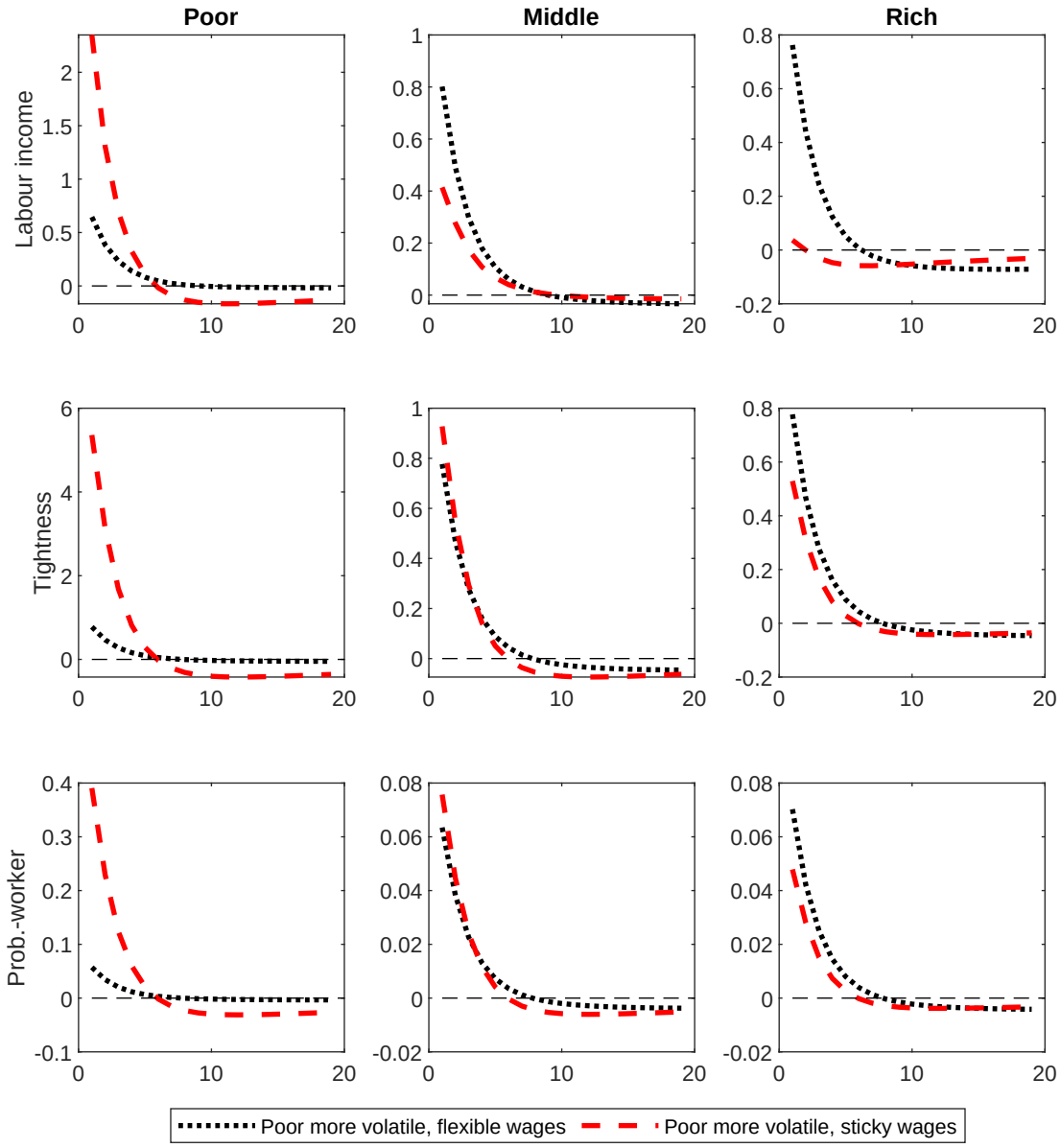
Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

The explanation for the result can be found by looking at Figures 9 and 10, where we see that with flexible wages, most of the difference in the labour response is concentrated in the segments of poor and rich workers, with the poor working less in the case of flexible wages and the rich working more (both compared to the sticky wage case). Part of the reason is that the rich households receive dividends, which fall in the case of flexible wages, increasing the labour supply of these households. A more important reason is that with flexible wages, the surplus of labour firms is less responsive for the poor compared to the benchmark case, and given our calibration, it is also equally responsive across all labour market segments.[33] As a

[33]Recall that this is because we calibrate vacancy posting costs in proportion to labour productivities of

result, labour market tightness in Figure 10 increases approximately equally across all labour market segments and is not disproportionally tilted towards the poor as in the benchmark case. Compared to the sticky wage case, more jobs go towards the rich and middle-income households, who have lower MPCs, so that the increase in aggregate demand, output, and employment is lower. The amplification effect due to disproportionate hiring in the poor labour market segment is also not as strong as in the benchmark case. Dividends fall because a higher wage increase is required to induce workers to supply more labour.

Figure 10: The role of wage rigidity 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.

households.

4.2 Calibration for the US and differentials in wage rigidities

So far, we have always assumed that wage rigidity is the same for all labour market segments, i.e., 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 the 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 this section looks into the effects of such differences.

First, recall that the evidence for the US reported in Figure 4 that suggests that wages are more sticky in the labour market for workers with low educational attainment. 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 12), 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.[34]

Table 12: 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

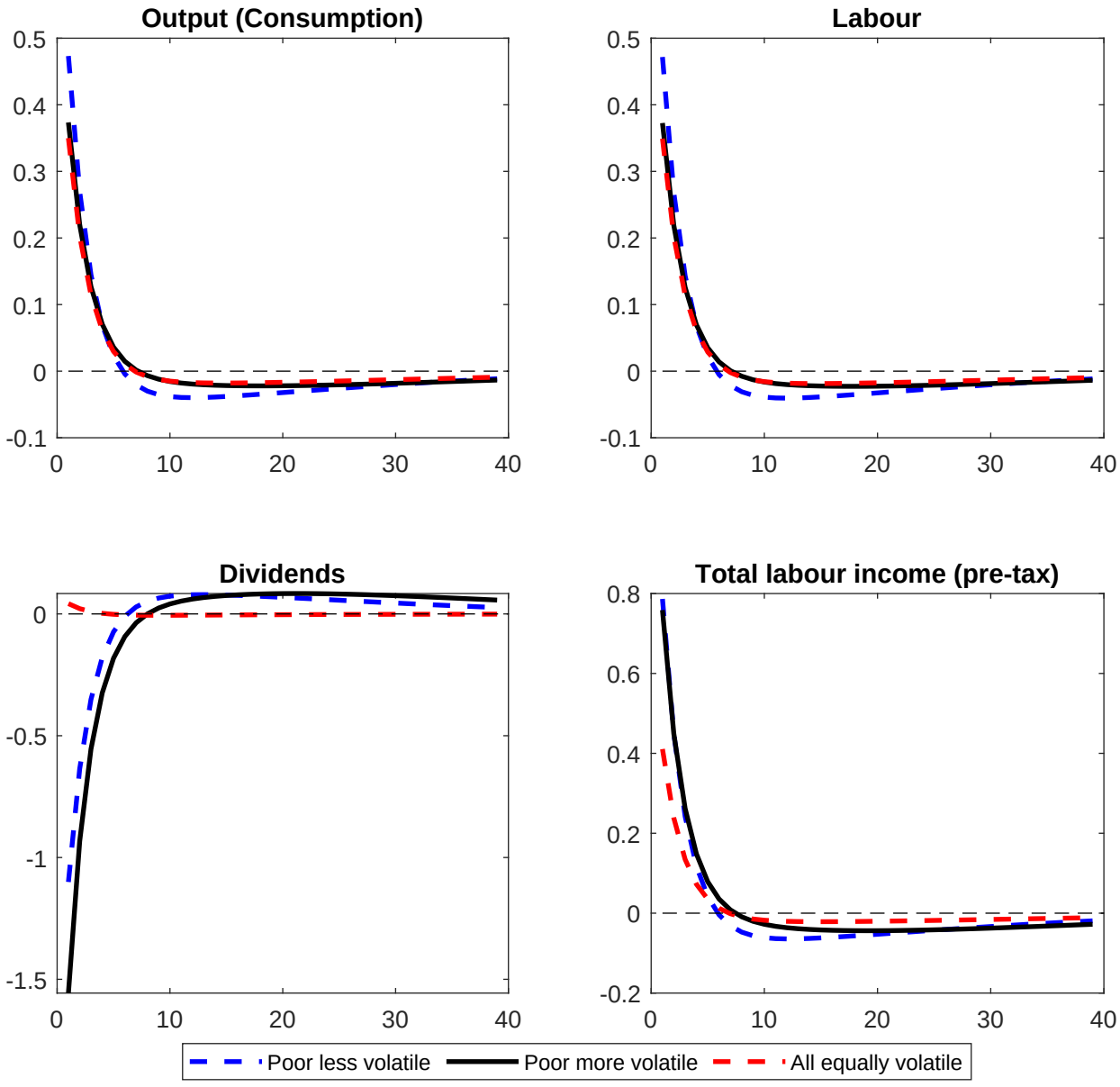
We repeat the simulation of an expansionary and persistent monetary policy shock across the three experiments. First, we consider the flexible-wage case, which is shown in Figures 11, 12 and 13 in full black lines. As one alternative, we assume wages are more rigid in the labour market segment of the 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 11 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 12 and 13 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

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

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).

Figure 11: Effectiveness of monetary policy depending on who gets jobs

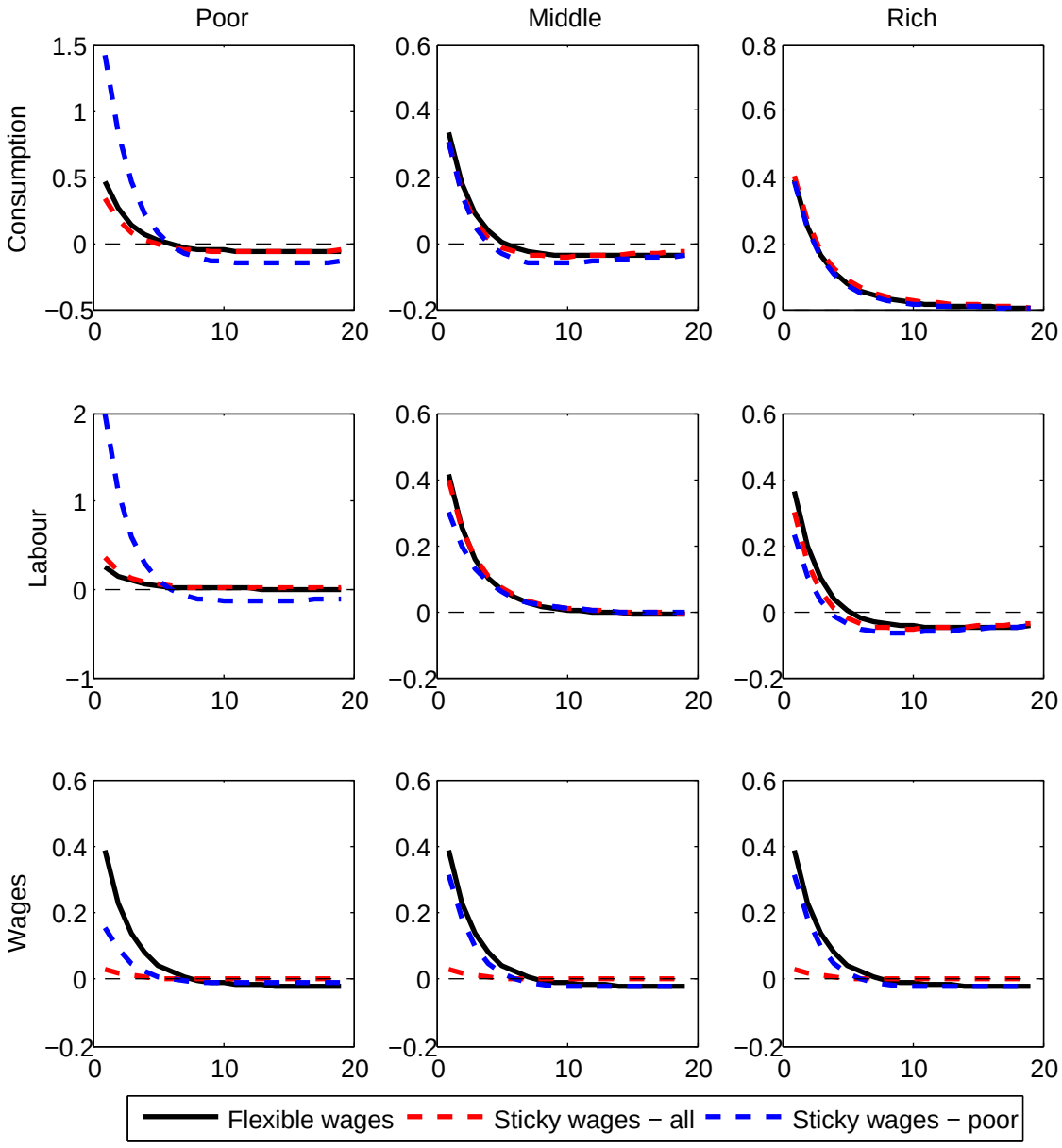


Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

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 amplified by the interaction both lower entrepreneur's share and higher wage stickiness in the labour market segment for the poor (dashed blue lines). Note that this result is not obvious, because more rigid wages for the poor also mean less wage-

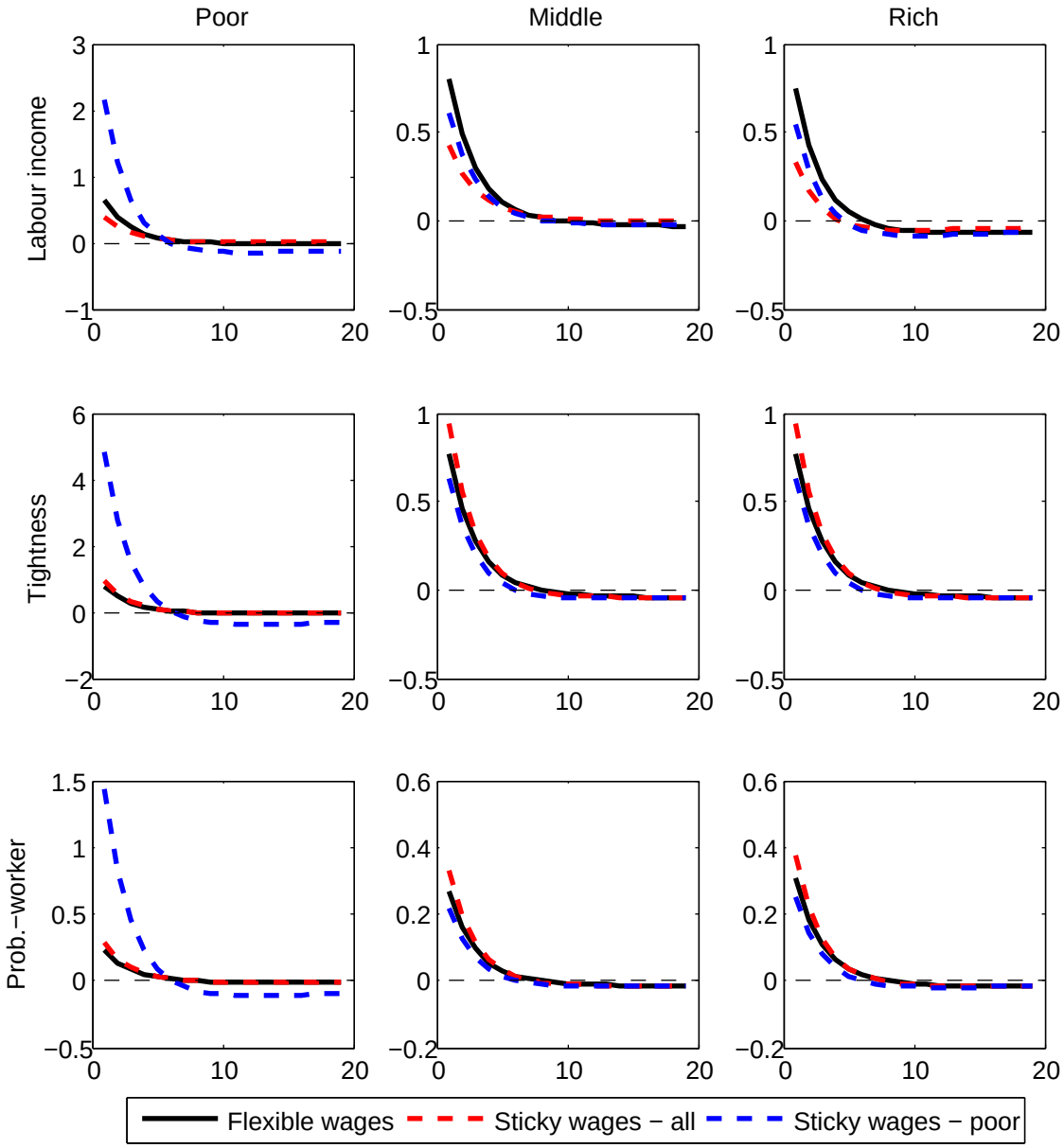
increase-related income. It is therefore crucial that in the case of more rigid wages of the poor the increase in employment is strong enough to dominate the lower increase in wages. Note also that the wealth effect on labour supply also works against the amplification. However, because the supply of searchers also depends on matching probability (and not only on wages), 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 12: 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 13: 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 labour market across educational attainment levels. We find that in several large European countries labour market at low educational attainment levels 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. At cyclical frequencies, fluctuations in job finding rates explain the majority of cyclical fluctuations in unemployment at the lower educational attainment levels, and the share of explained fluctuations can exceed 80% in countries such as Germany and France. Cyclical fluctuations in separation rates tend to be less important in explaining fluctuations in unemployment, especially at lower educational attainment levels. The situation is similar in the US.

We then construct a stylised incomplete markets model with the search-and-matching framework for segmented labour markets for workers 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. 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, or both.

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A Additional empirical evidence from European countries

A.1 Job finding rates and separation rates by educational attainment in Europe

A.1.1 Unemployment duration spell less than 3 months (d<3)

Figure 14: France

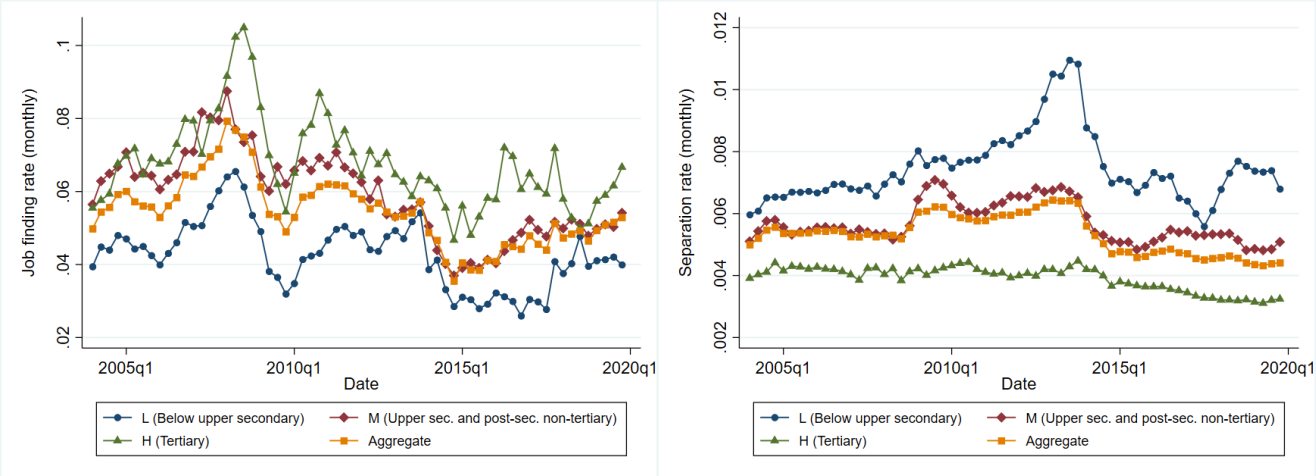


Figure 15: Germany

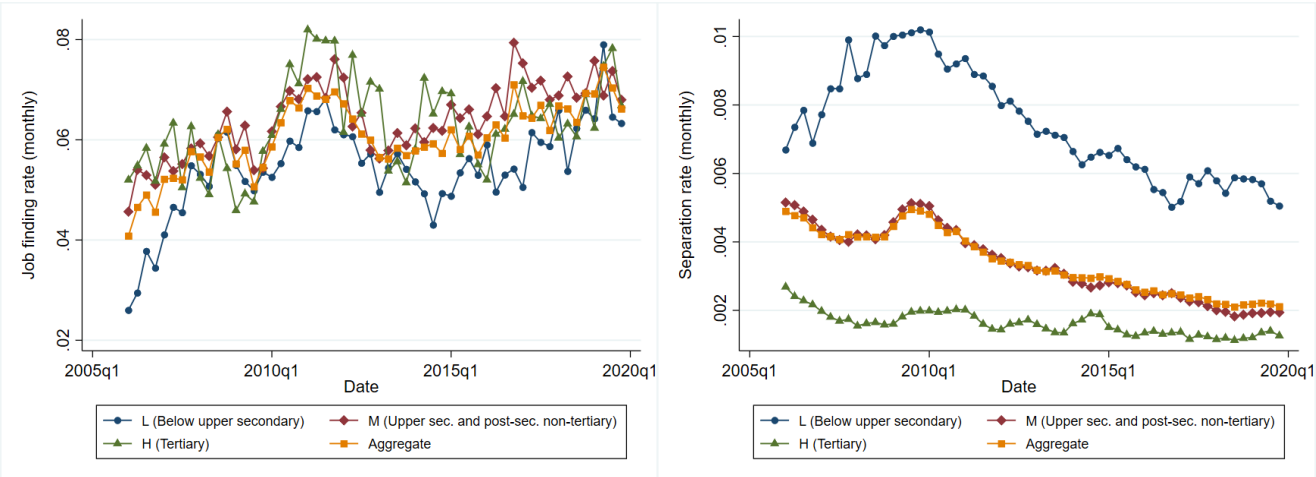


Figure 16: Greece

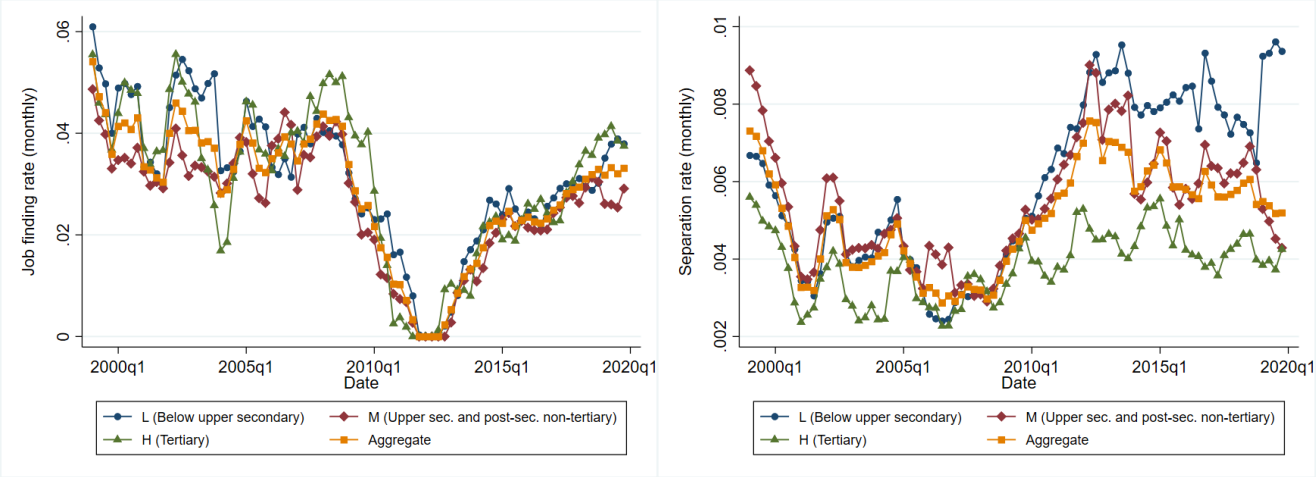


Figure 17: Ireland

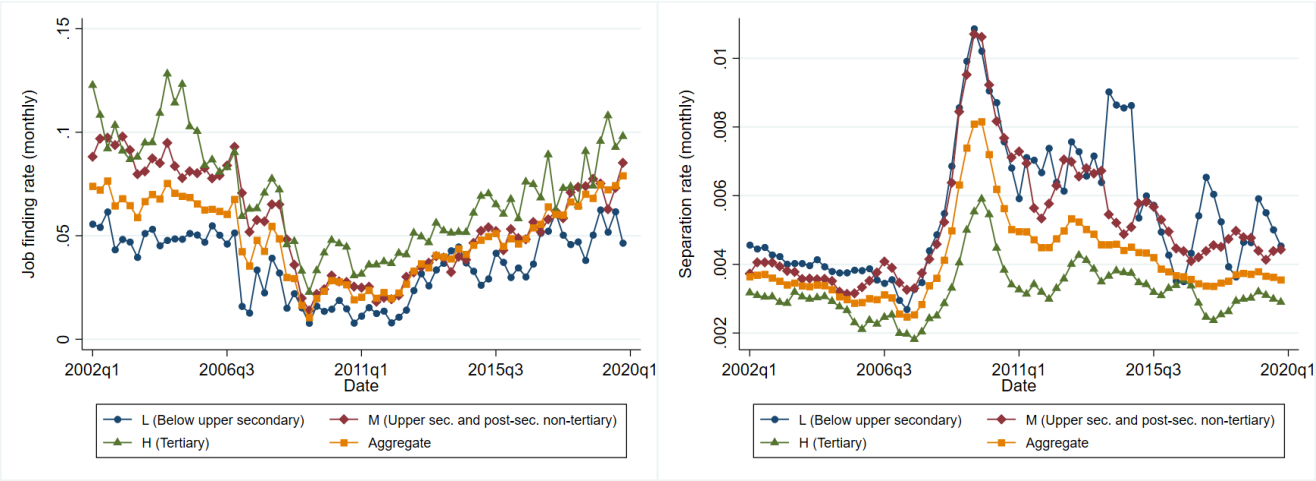


Figure 18: Italy

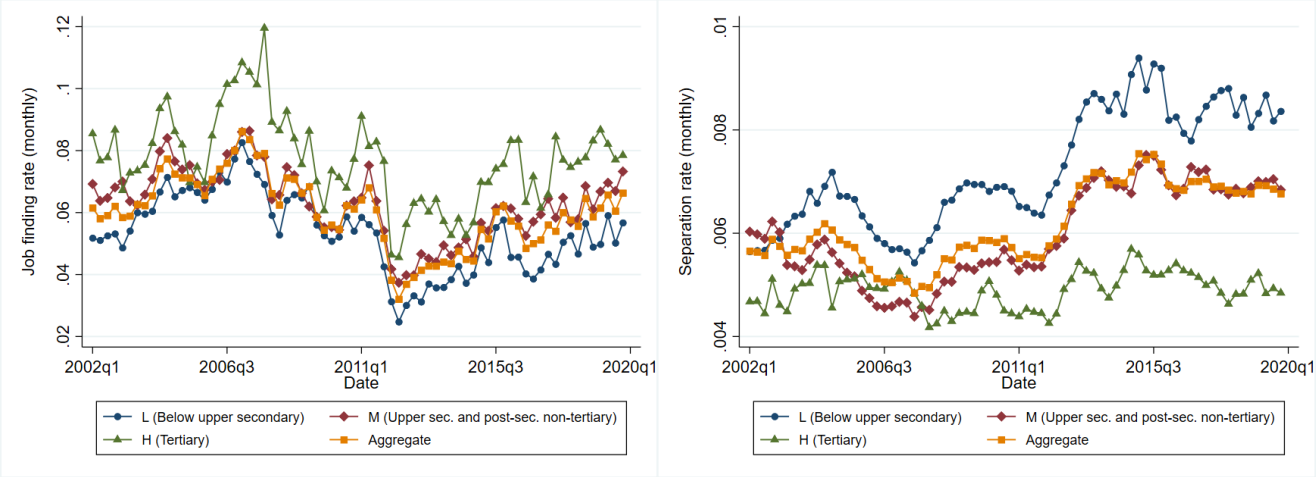


Figure 19: Spain

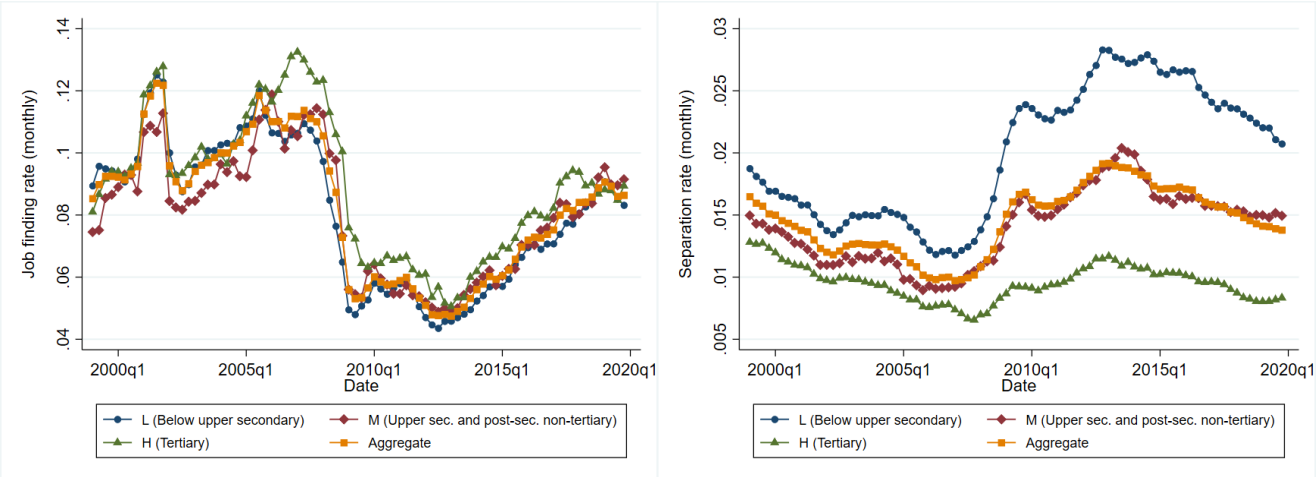
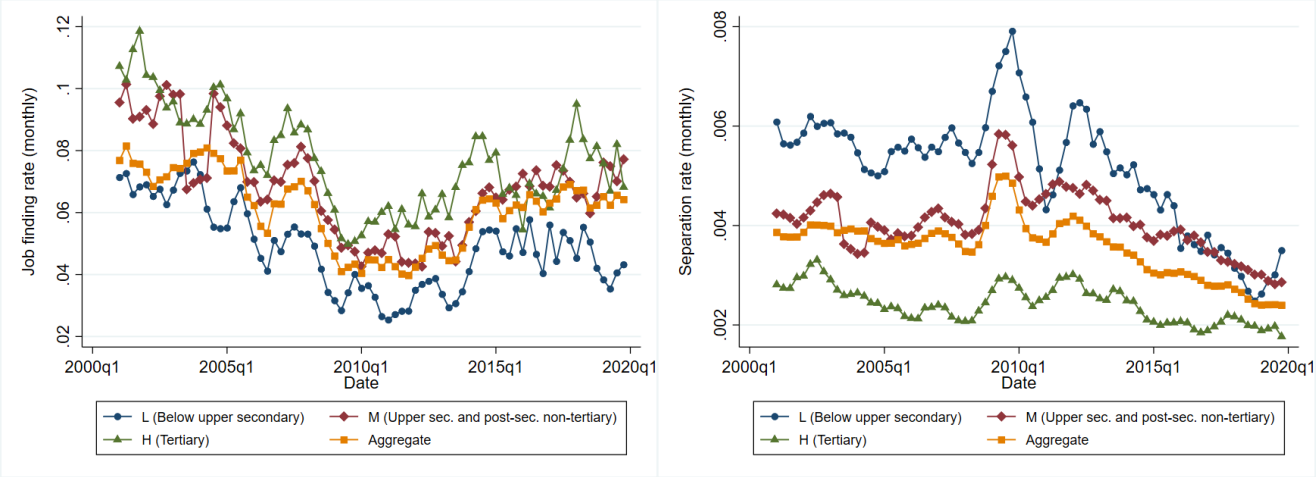


Figure 20: UK



A.1.2 Unemployment duration spell less than 6 months (d<6)

Figure 21: France

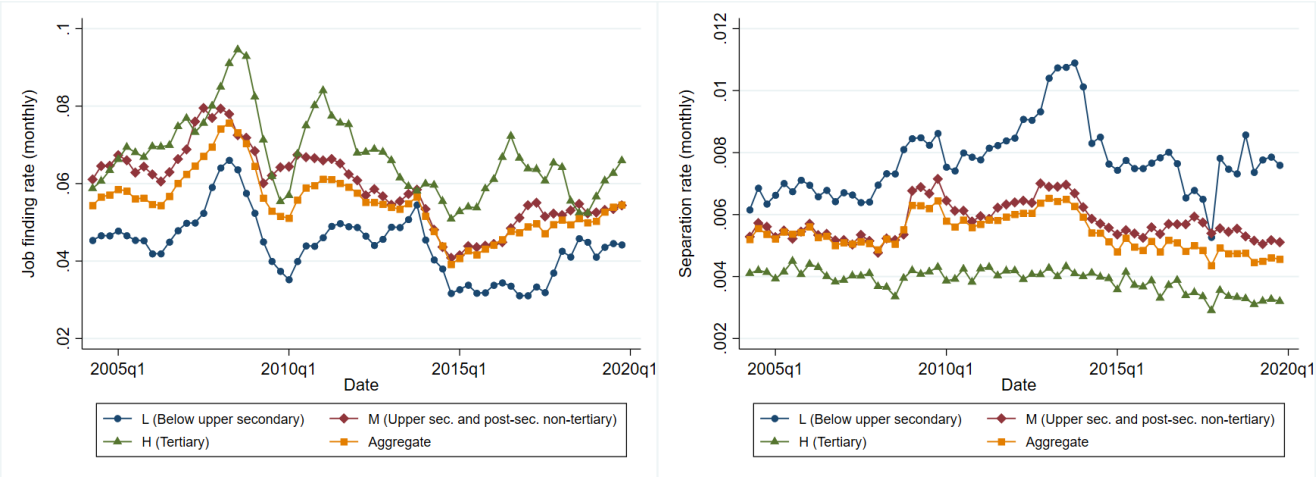


Figure 22: Germany

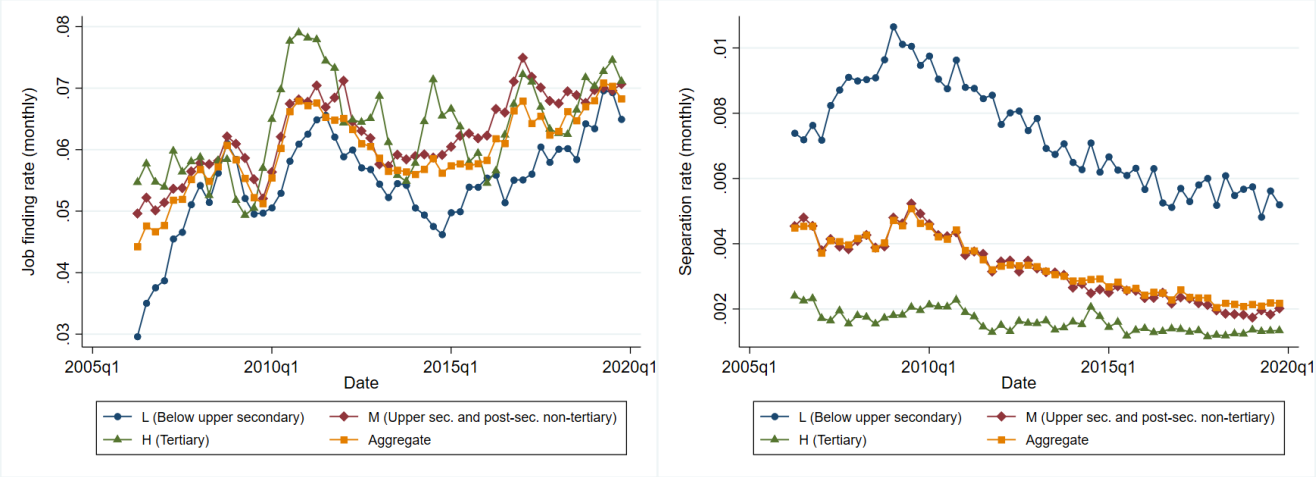


Figure 23: Greece

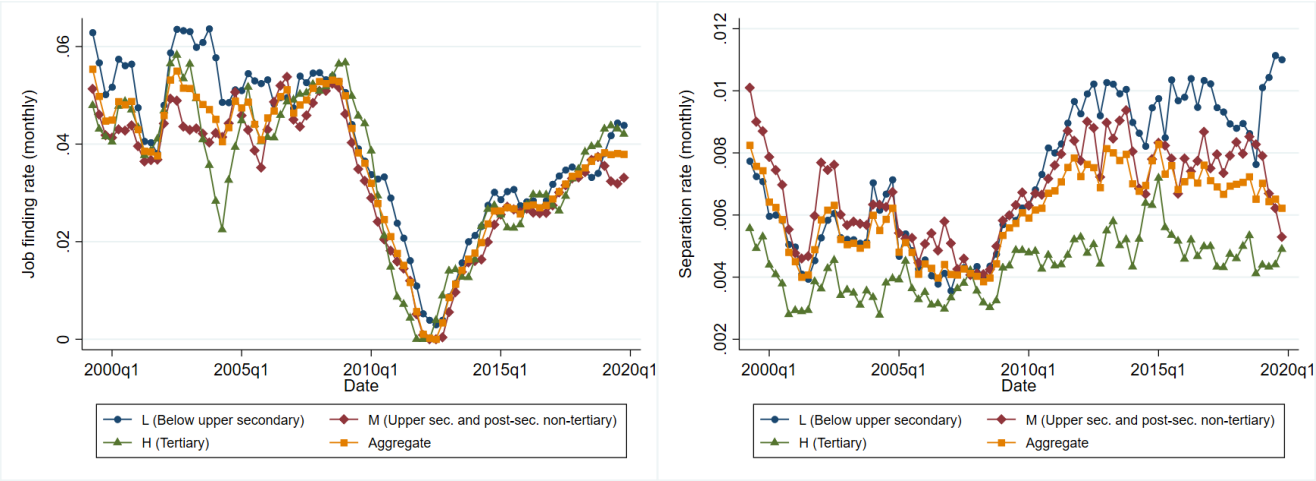


Figure 24: Ireland

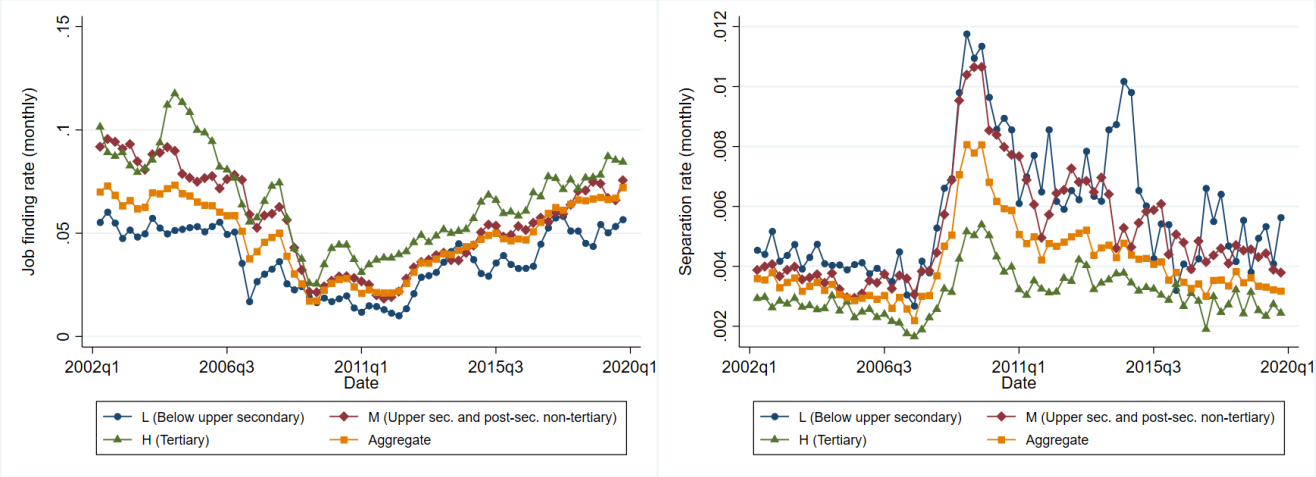


Figure 25: Italy

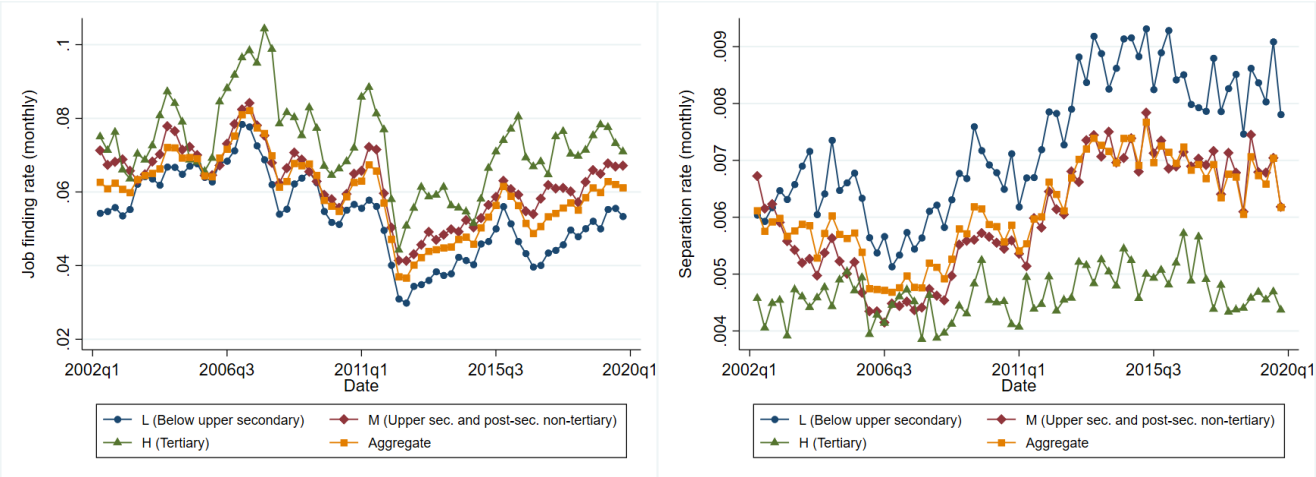


Figure 26: Spain

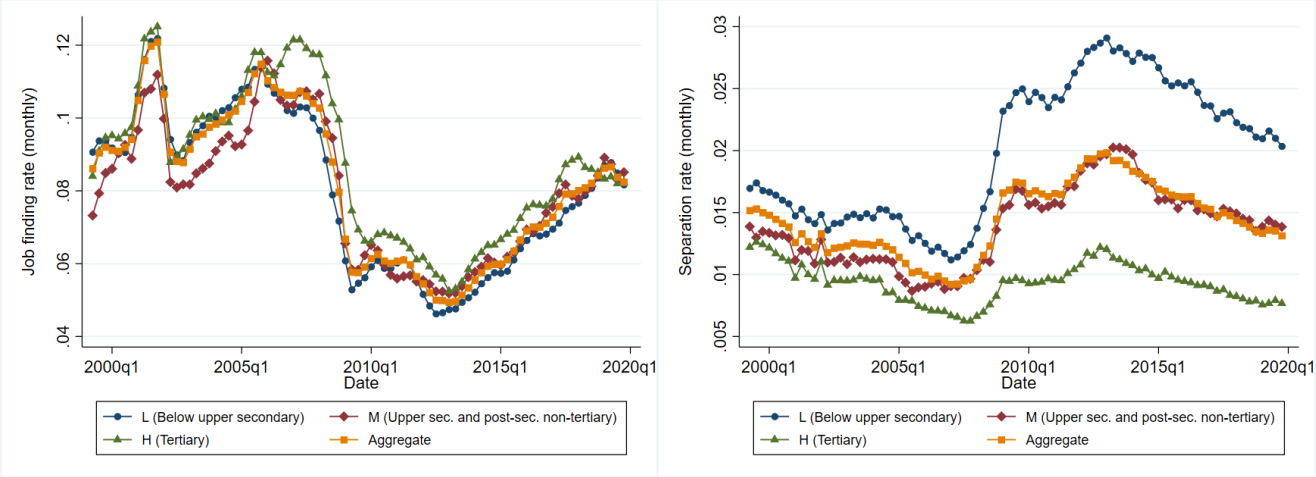
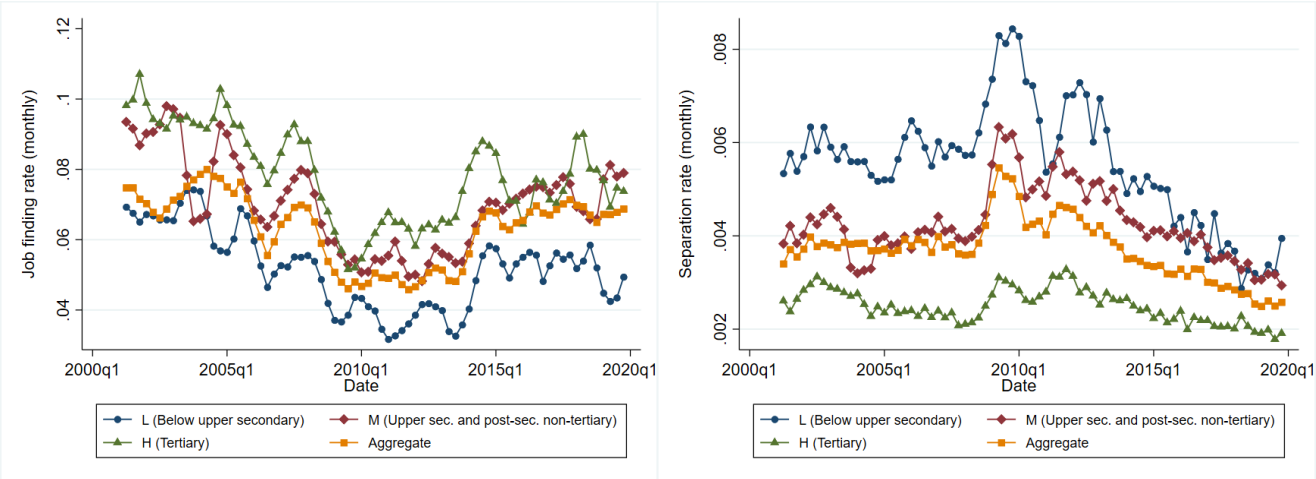


Figure 27: UK



A.1.3 Unemployment duration spell less than 12 months (d<12)

Figure 28: France

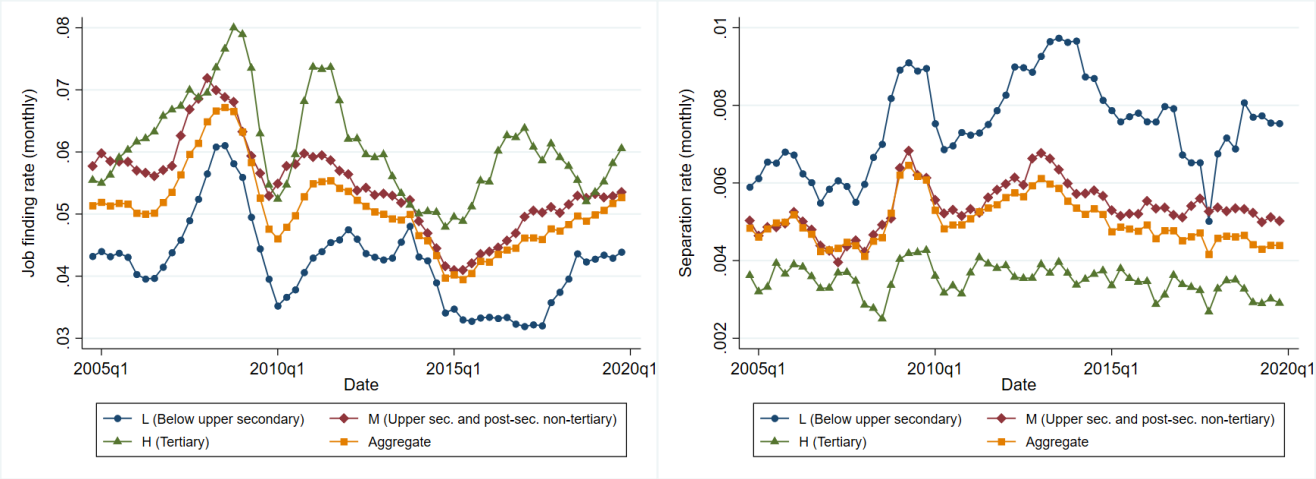


Figure 29: Germany

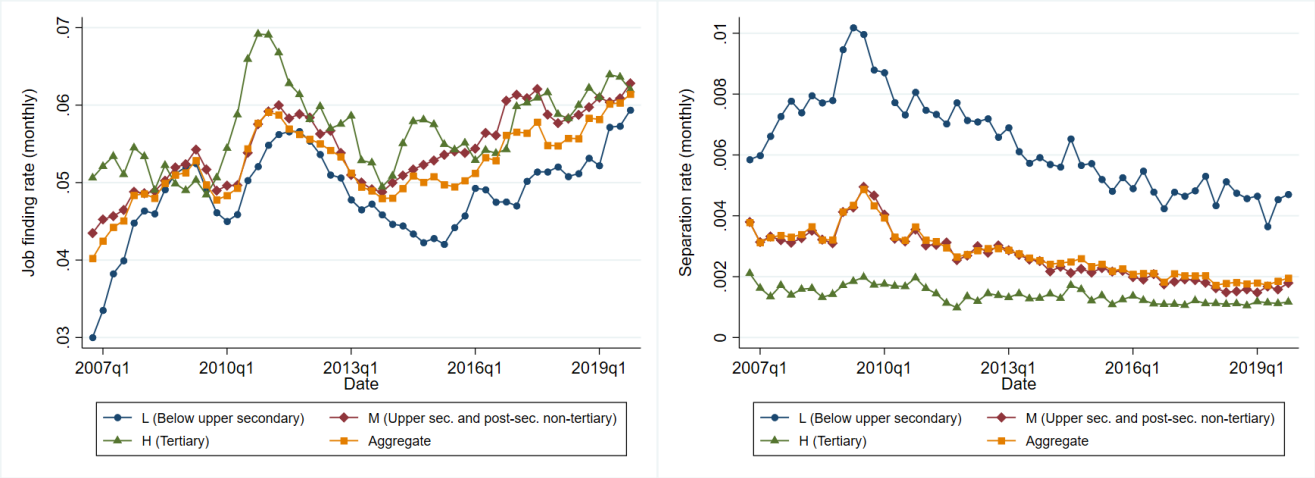


Figure 30: Greece

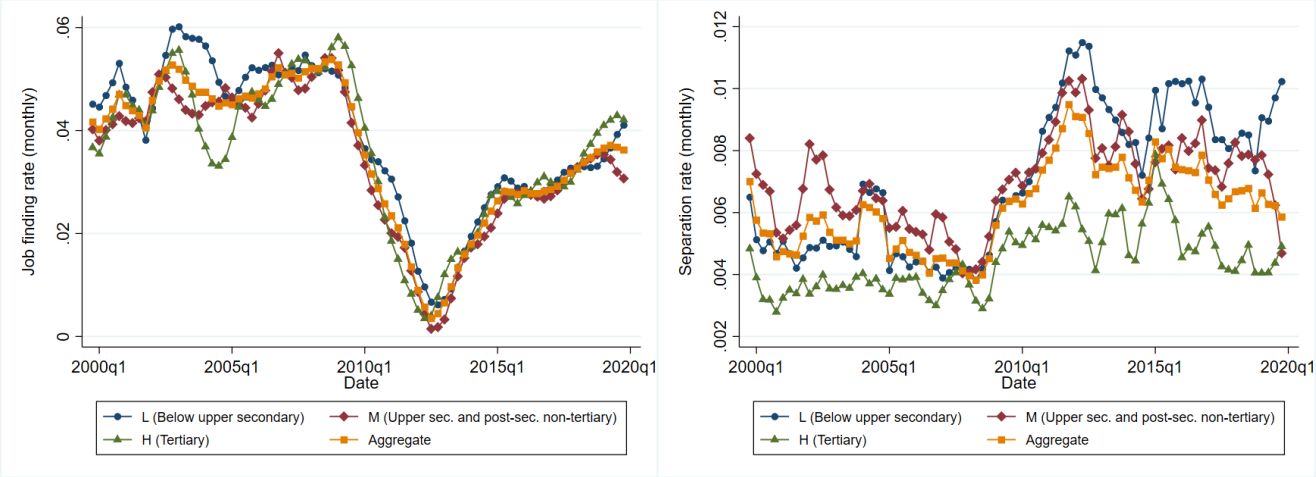


Figure 31: Ireland

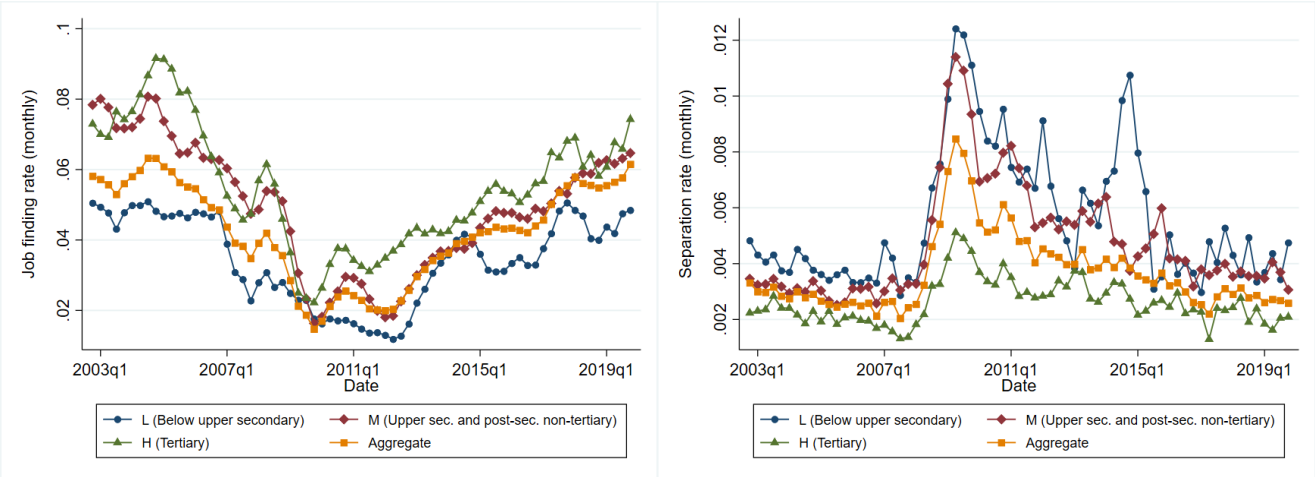


Figure 32: Italy

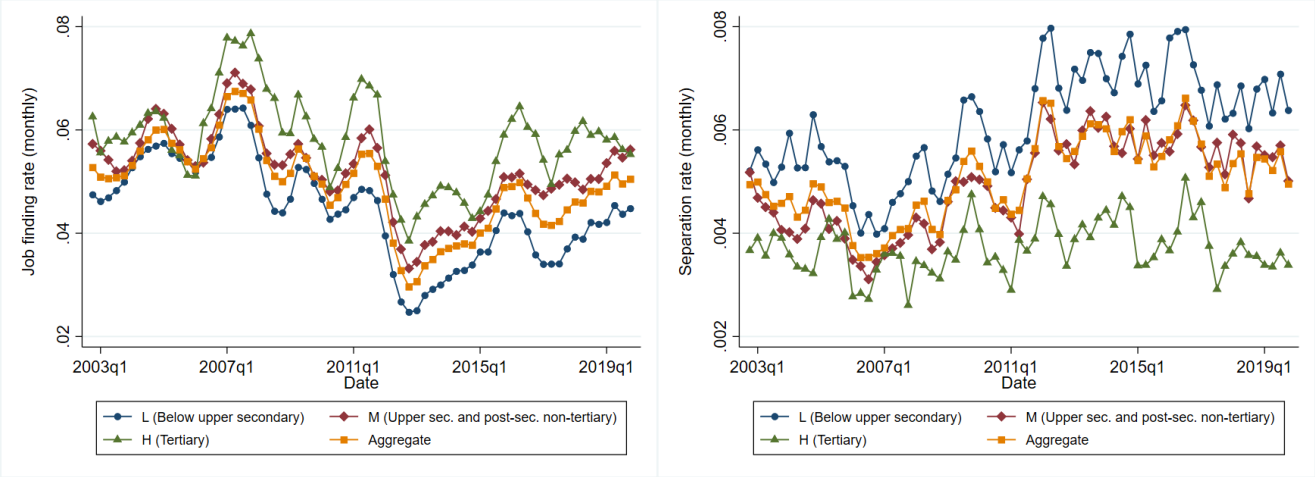


Figure 33: Spain

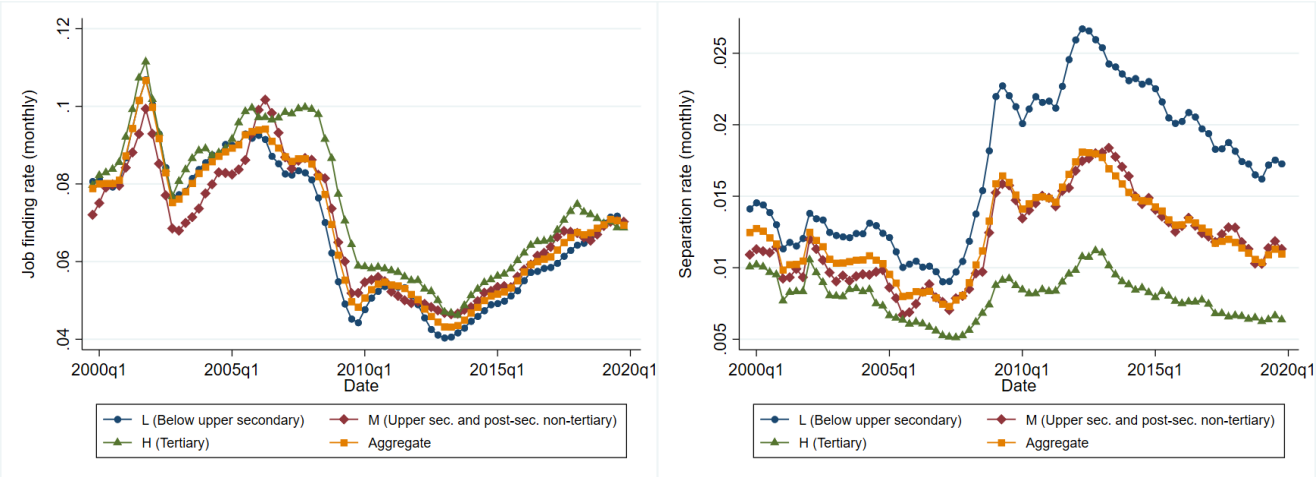
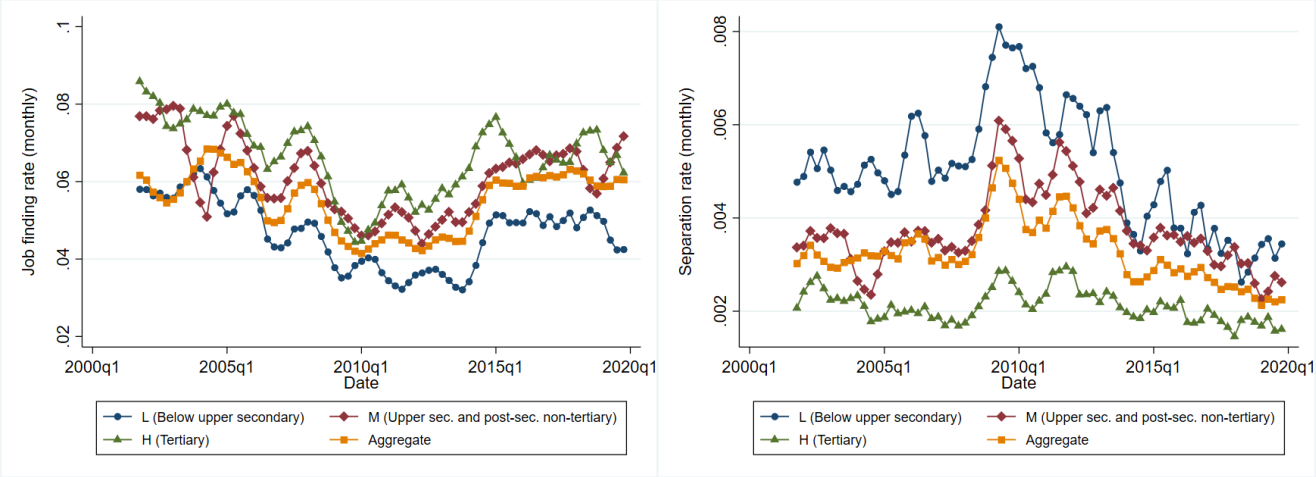


Figure 34: UK


Job finding rate (monthly)
.02
.04
.06
.08
.1
2000q1
2005q1
2010q1
2015q1
2020q1
Date
L (Below upper secondary)
M (Upper sec. and post-sec. non-tertiary)
H (Tertiary)
Aggregate
Separation rate (monthly)
.002
.004
.006
.008
2000q1
2005q1
2010q1
2015q1
2020q1
Date
L (Below upper secondary)
M (Upper sec. and post-sec. non-tertiary)
H (Tertiary)
Aggregate

A.2 Job finding probabilities and separation probabilities across European countries

While the main text reports monthly job finding rates to be consistent with the literature (Fujita and Ramey (2009), Shimer (2012)), it is sometimes convenient to have quarterly probabilities, in particular, when calibrating models that are typically at a quarterly frequency. This appendix reports the companion set of business cycle statistics in terms of quarterly probabilities.[35]

Table 13: Quarterly job finding probabilities

		$F^{<3}$			$F^{<6}$			$F^{<12}$		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	0.12	0.16	0.18	0.12	0.16	0.18	0.12	0.15	0.17
Germany	2005Q1-2019Q4	0.15	0.17	0.17	0.15	0.17	0.17	0.14	0.15	0.16
Greece	1998Q1-2019Q4	0.09	0.08	0.09	0.11	0.10	0.10	0.11	0.10	0.10
Ireland	2001Q1-2019Q4	0.10	0.16	0.19	0.11	0.16	0.18	0.10	0.14	0.15
Italy	2001Q1-2019Q4	0.15	0.17	0.21	0.15	0.17	0.20	0.13	0.15	0.16
Spain	1998Q1-2019Q4	0.22	0.22	0.23	0.21	0.21	0.23	0.18	0.19	0.20
UK	2000Q1-2019Q4	0.14	0.19	0.21	0.15	0.19	0.21	0.13	0.18	0.18

Notes: The table reports quarterly job finding probabilities associated with the estimated monthly job finding rates f_t, computed as $F_t = 1 - e^{-3f_t}$, where F_t 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

Table 14: Quarterly separation probabilities

		$S^{<3}$			$S^{<6}$			$S^{<12}$		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	0.020	0.017	0.012	0.021	0.017	0.012	0.020	0.016	0.011
Germany	2005Q1-2019Q4	0.021	0.010	0.005	0.021	0.010	0.005	0.018	0.008	0.004
Greece	1998Q1-2019Q4	0.015	0.017	0.012	0.019	0.021	0.014	0.018	0.021	0.014
Ireland	2001Q1-2019Q4	0.014	0.016	0.010	0.015	0.016	0.010	0.014	0.014	0.008
Italy	2001Q1-2019Q4	0.021	0.018	0.015	0.021	0.018	0.015	0.018	0.015	0.012
Spain	1998Q1-2019Q4	0.057	0.042	0.029	0.057	0.042	0.029	0.049	0.036	0.025
UK	2000Q1-2019Q4	0.015	0.012	0.008	0.016	0.013	0.008	0.014	0.011	0.007

Notes: The table reports quarterly separation probabilities associated with the estimated monthly separation rates s_t, computed as $S_t = 1 - e^{-3s_t}$, where S_t is the probability that an employed worker loses a job in the 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

[35] While quantitatively not important, note that the transformation from monthly rates to quarterly probabilities is nonlinear. If x is rate and X is probability, the formula is $X = 1 - e^{-3x}$.

Table 15: Cyclical properties of job finding probabilities, quarterly

		Rel. own vol. $\sigma(F_i)/\sigma(U_i)$			Rel. aggregate vol. $\sigma(F_i)/\sigma(U)$			Corr. with agg. unemployment		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	36.54	28.35	34.13	39.25	29.42	45.72	-0.60	-0.43	-0.55
Germany	2005Q1-2019Q4	42.06	31.02	39.72	40.40	34.50	56.94	-0.46	-0.20	-0.07
Greece	1998Q1-2019Q4	22.23	16.55	25.22	21.31	17.79	26.71	-0.40	-0.43	-0.42
Ireland	2001Q1-2019Q4	24.41	17.91	21.74	21.45	20.29	25.11	-0.36	-0.71	-0.44
Italy	2001Q1-2019Q4	29.32	30.17	39.44	30.47	29.97	45.36	-0.23	-0.41	-0.49
Spain	1998Q1-2019Q4	19.64	24.11	24.22	20.93	22.66	24.13	-0.61	-0.71	-0.81
UK	2000Q1-2019Q4	33.17	29.69	26.77	29.56	33.31	36.80	-0.33	-0.44	-0.30

Notes: The table reports standard deviations of cyclical components of quarterly job finding probabilities, computed as $F_t = 1 - e^{-3f_t}$, relative to the standard deviation of the cyclical component of each group's unemployment U_i, aggregate unemployment U, and correlations of cyclical components of quarterly job finding probabilities with the cyclical component of aggregate 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

Table 16: Cyclical properties of separation probabilities, quarterly

		Rel. own vol. $\sigma(S_i)/\sigma(U_i)$			Rel. aggregate vol. $\sigma(S_i)/\sigma(U)$			Corr. with agg. unemployment		
Country	Sample	L	M	H	L	M	H	L	M	H
France	2003Q1-2019Q4	3.00	2.43	0.86	3.22	2.53	1.15	-0.07	0.09	0.31
Germany	2005Q1-2019Q4	4.31	2.20	0.95	4.14	2.45	1.36	0.01	0.65	0.52
Greece	1998Q1-2019Q4	2.09	2.67	1.72	2.00	2.88	1.83	0.31	0.25	0.10
Ireland	2001Q1-2019Q4	2.80	2.31	1.47	2.46	2.62	1.70	0.56	0.58	0.62
Italy	2001Q1-2019Q4	1.91	1.52	1.31	1.98	1.51	1.50	0.67	0.60	0.39
Spain	1998Q1-2019Q4	3.63	2.68	1.47	3.87	2.52	1.46	0.83	0.81	0.81
UK	2000Q1-2019Q4	2.40	1.48	0.82	2.14	1.66	1.13	0.23	0.47	0.66

Notes: The table reports standard deviations of cyclical components of quarterly separation probabilities, computed as $S_t = 1 - e^{-3s_t}$, relative to the standard deviation of the cyclical component of each group's unemployment U_i, aggregate unemployment U, and correlations of cyclical components of quarterly separation probabilities with the cyclical component of aggregate 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. We end the sample in Q4 2019 to exclude the COVID-19 period.

B Responses of job finding rates and separation rates to a monetary tightening

B.1 Local projections specification

In the main text, we reported impulse responses of job finding and separation rates in selected euro area countries, using the following panel local projections specification

$$F_{i,t+h} = \alpha_i + \tau_h t + \varphi_h \, \nu_t + \sum_{q=1}^{Q} \omega_{h,q}^{F} \, F_{i,t-q} \; + \sum_{k=1}^{K} \omega_{h,k}^{C} \, C_{t-k} + \; \epsilon_{i,t+h} \; , \tag{37}$$

where, F_t is the job finding or separation rate, α_i are country-fixed effects, τ_h is the coefficient on the linear time trend, ν_t is the series of monetary policy shocks, and C_t is the log of euro area unemployment. The projection horizon is 12 quarters ($h = 0, ..., 12$). Because we have quarterly data, we opt for 4 lags in both the lagged dependent variable and in the controls ($K = Q = 4$). The impulse responses are constructed based on the estimated coefficient φ_h. Because we have a small and short sample (small n and T), inference is based on wild bootstrap cluster robust standard errors (Roodman et al. (2019)).

For country-specific impulse responses, we run local projections for each educational attainment level (within a country) separately

$$F_{t+h} = \alpha_h + \tau_h t + \varphi_h \, \nu_t + \sum_{q=1}^{Q} \omega_{h,q}^{F} \, F_{t-q} \; + \sum_{k=1}^{K} \omega_{h,k}^{C} \, C_{t-k} + \; \epsilon_{t+h} \; , \tag{38}$$

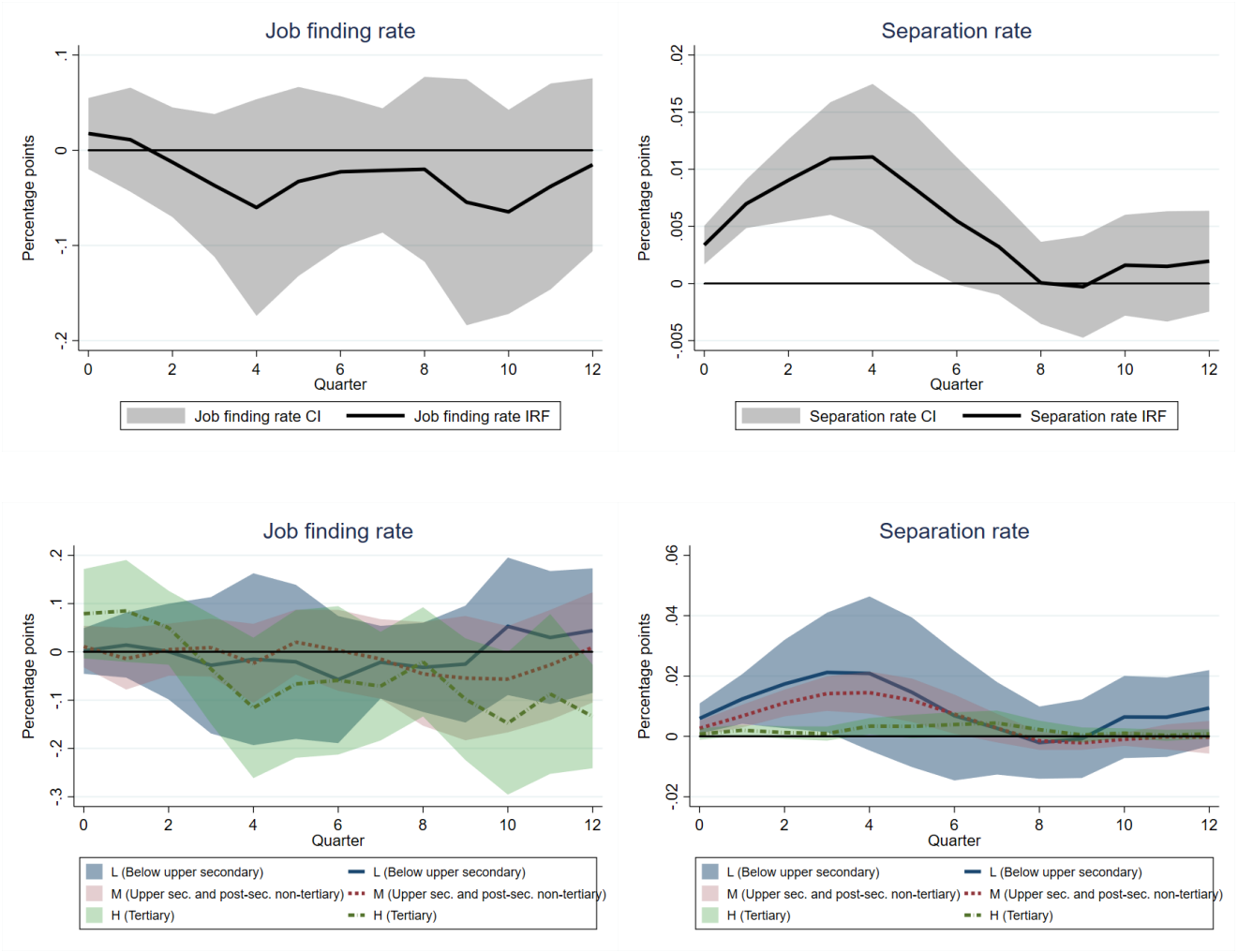
As before, F_t is the job finding or separation rate, τ_h is the coefficient on the linear time trend, ν_t is the series of monetary policy shocks, and C_t is the log of unemployment. Again, the projection horizon is 12 quarters, and we opt for 4 lags in the lagged dependent variable and the controls. The impulse responses are constructed based on the estimated coefficient φ_h. Standard errors are adjusted for heteroskedasticity and autocorrelation (Newey–West standard errors).

B.2 Impulse respones

Here we report the country-specific responses, estimated using country-by-country data. For each country, the first two panels report the impulse response estimated on the average data (the overall educational attainment levels), and the lower two panels report the impulse responses estimated for each educational attainment separately.

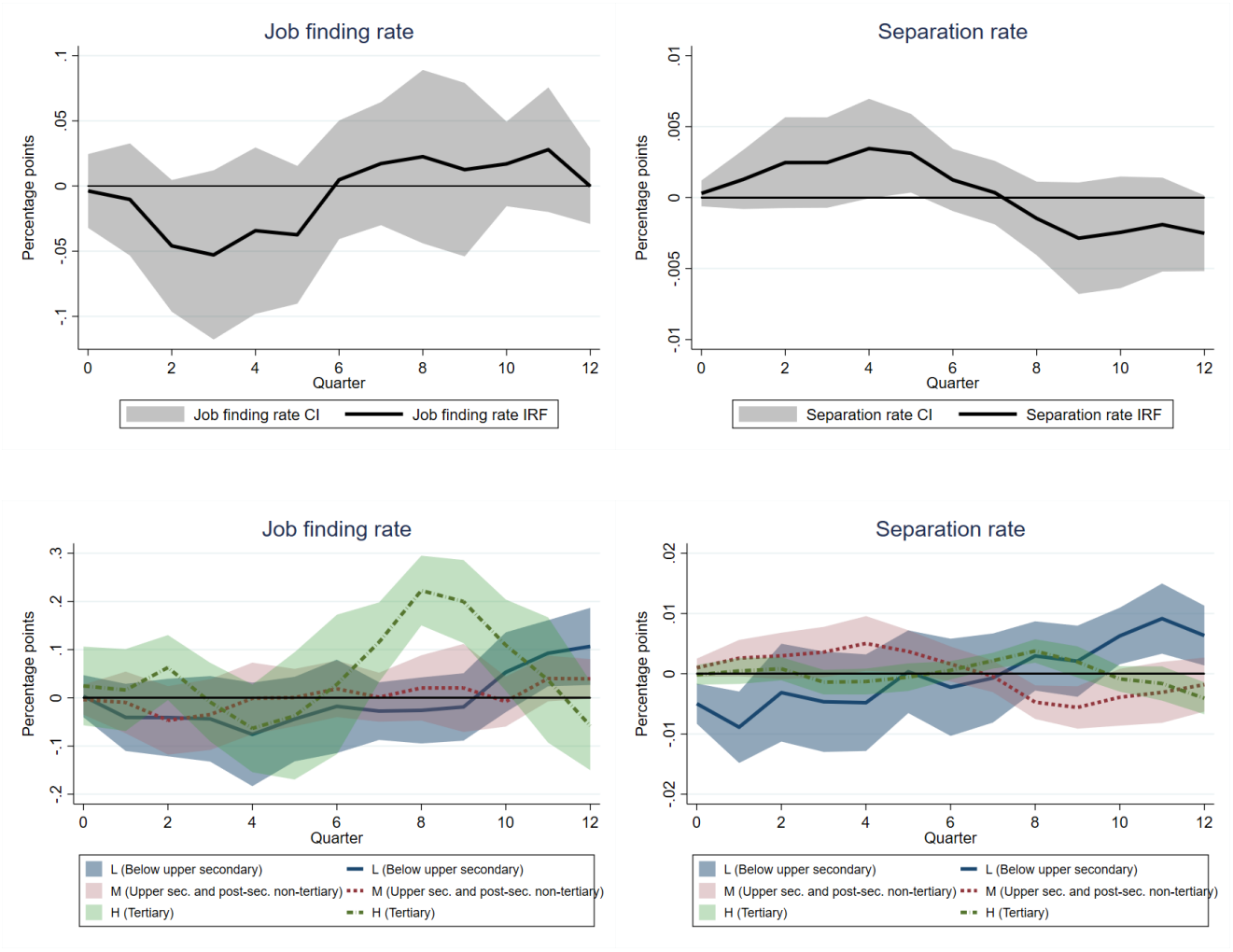
B.2.1 Unemployment duration spell less than 3 months (d<3)

Figure 35: France



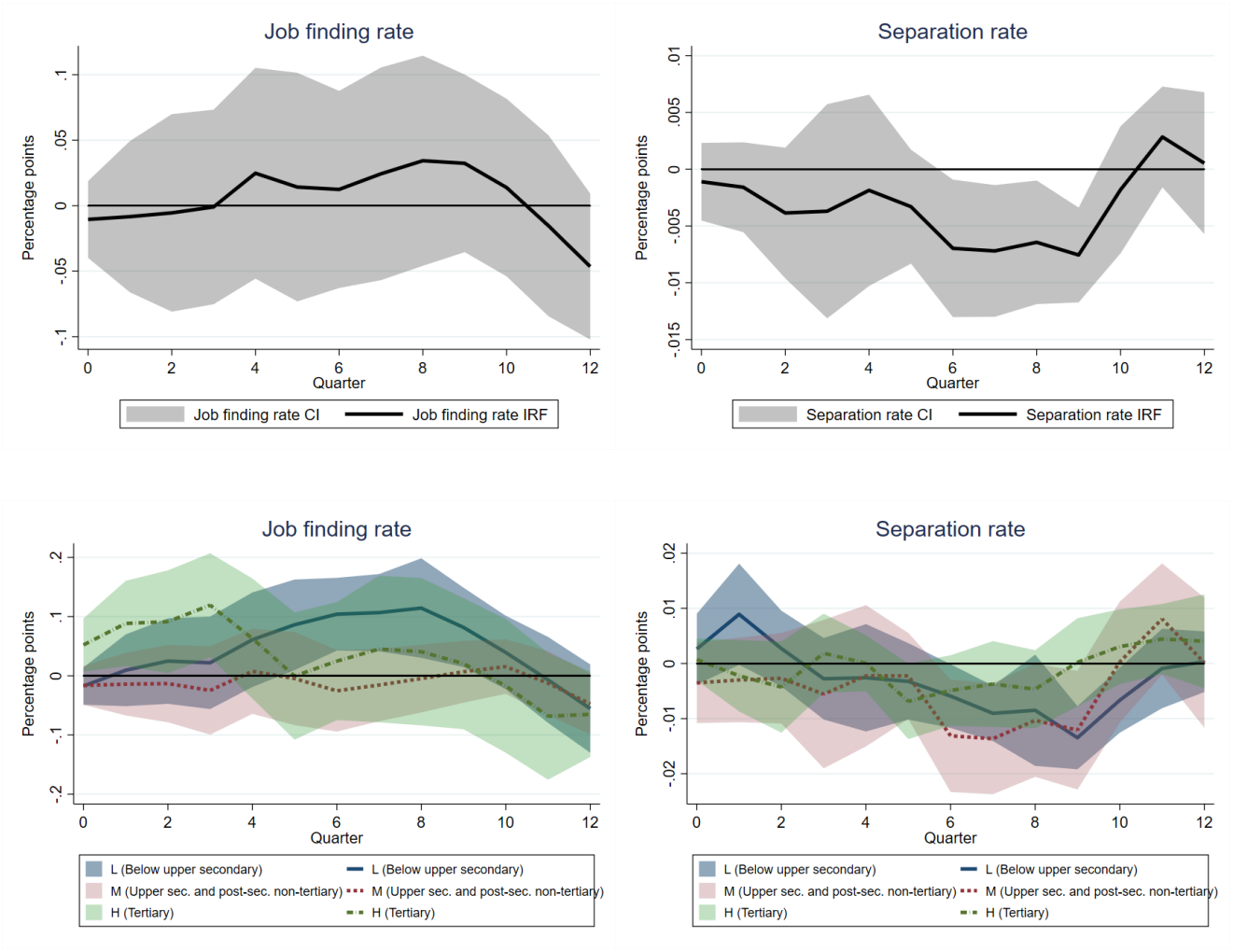
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 36: Germany



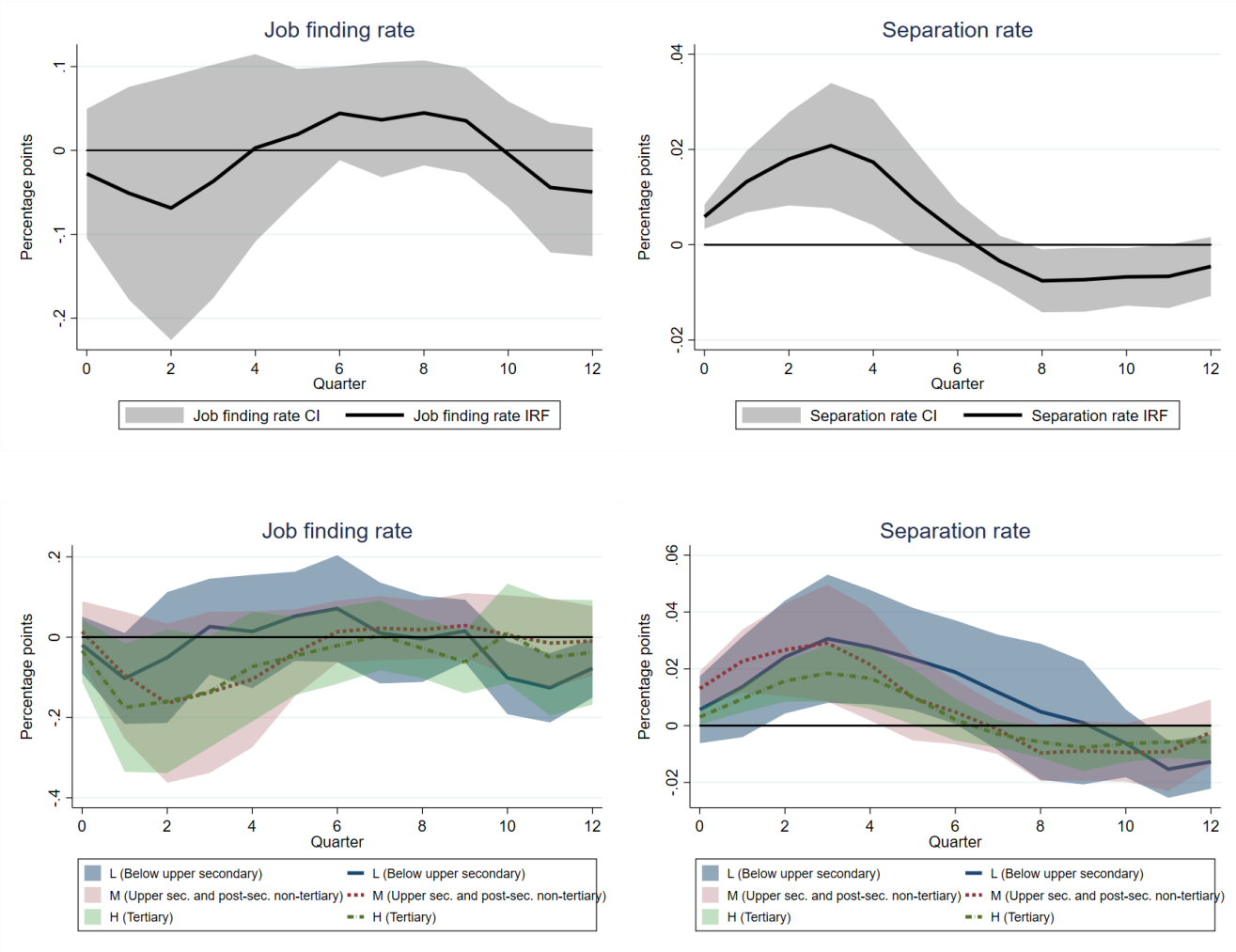
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 37: Greece



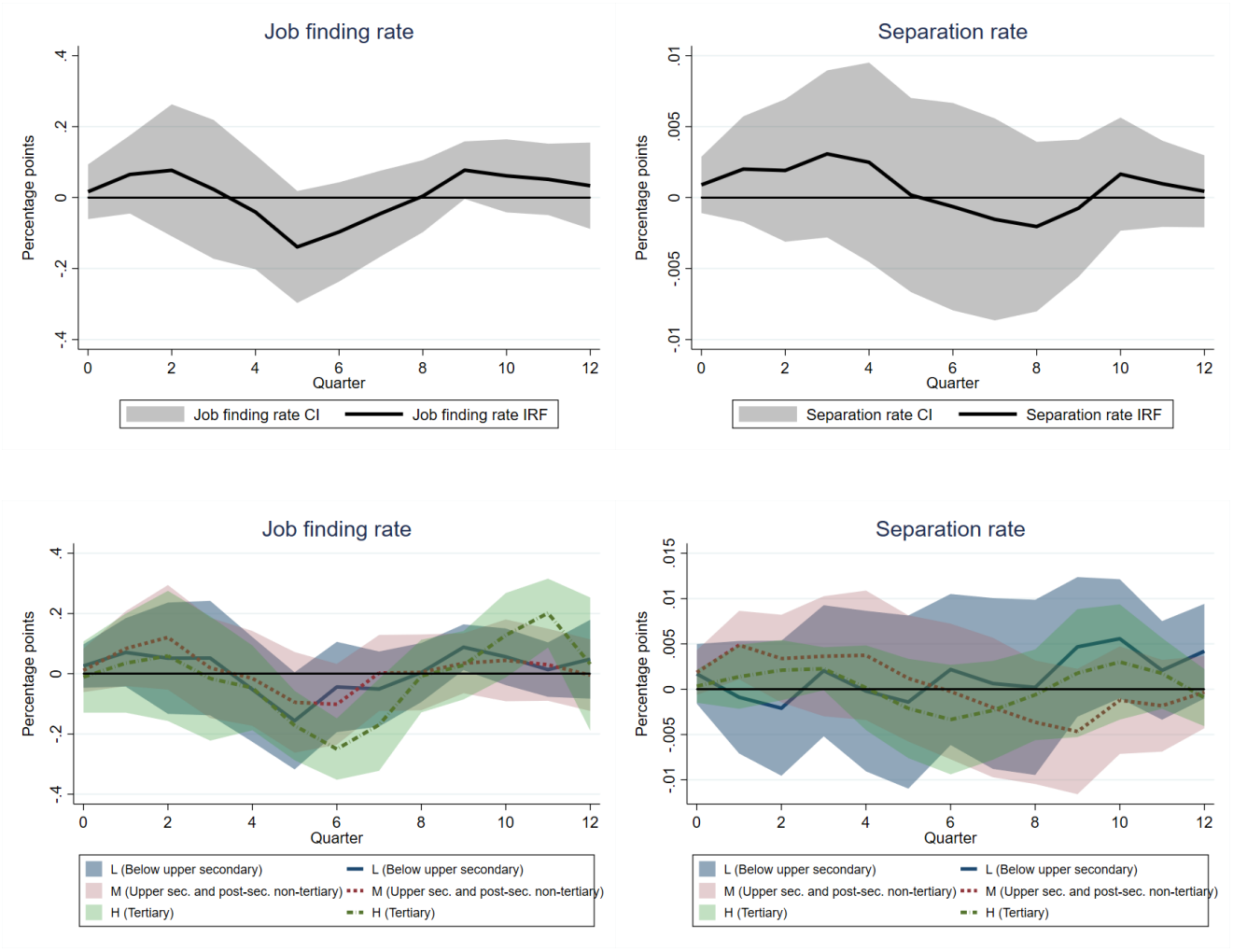
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 38: Ireland



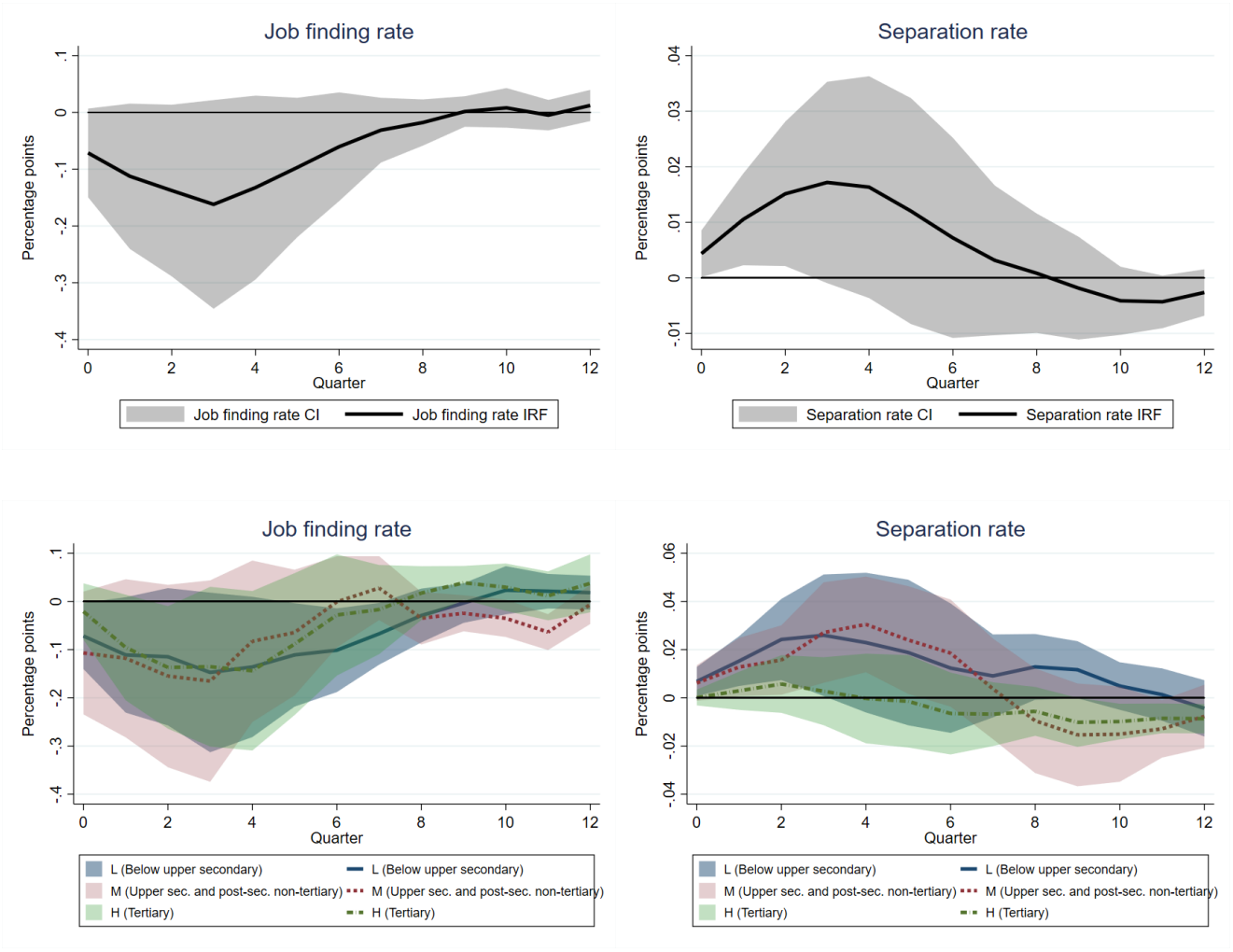
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 39: Italy



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

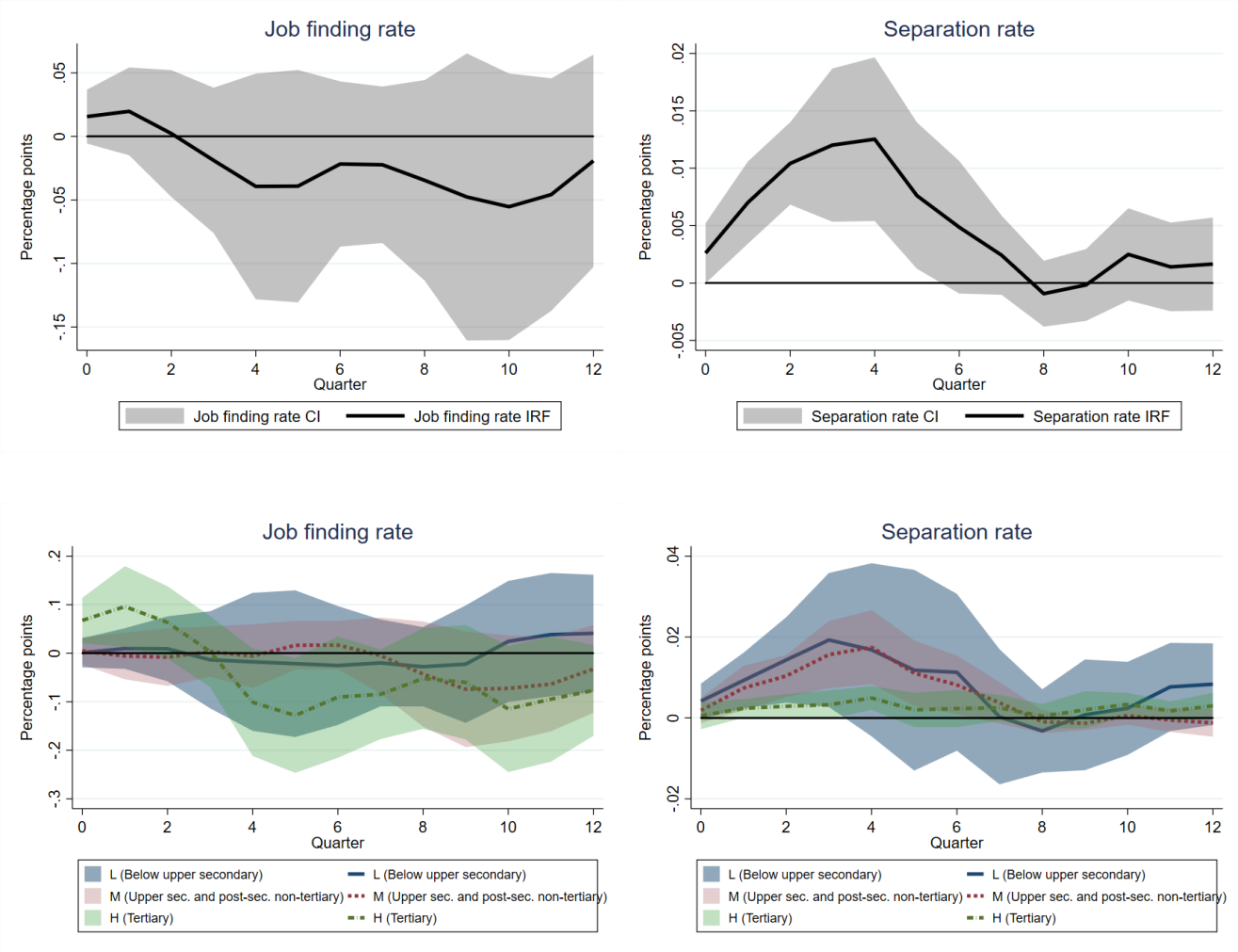
Figure 40: Spain



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

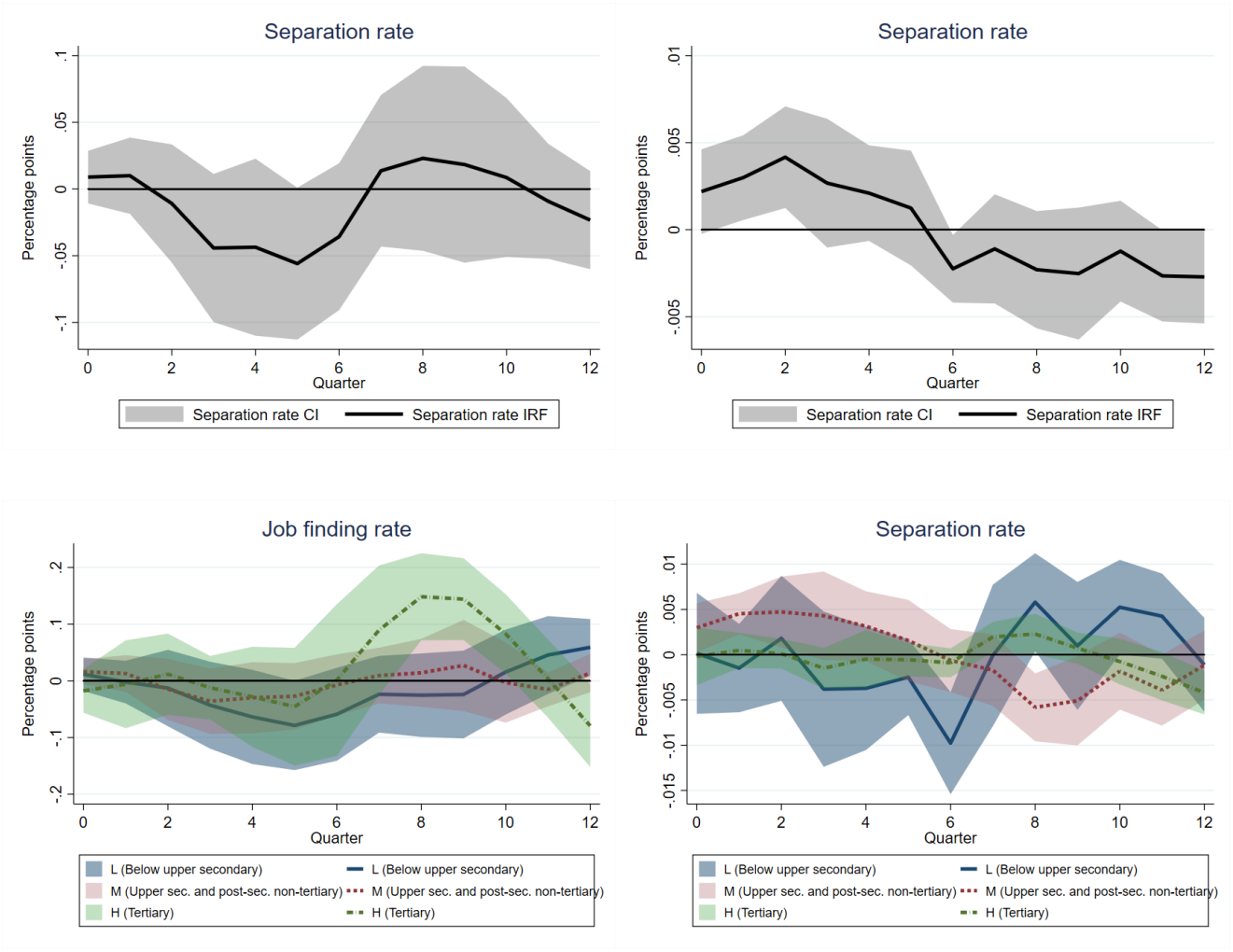
B.2.2 Unemployment duration spell less than 6 months (d<6)

Figure 41: France



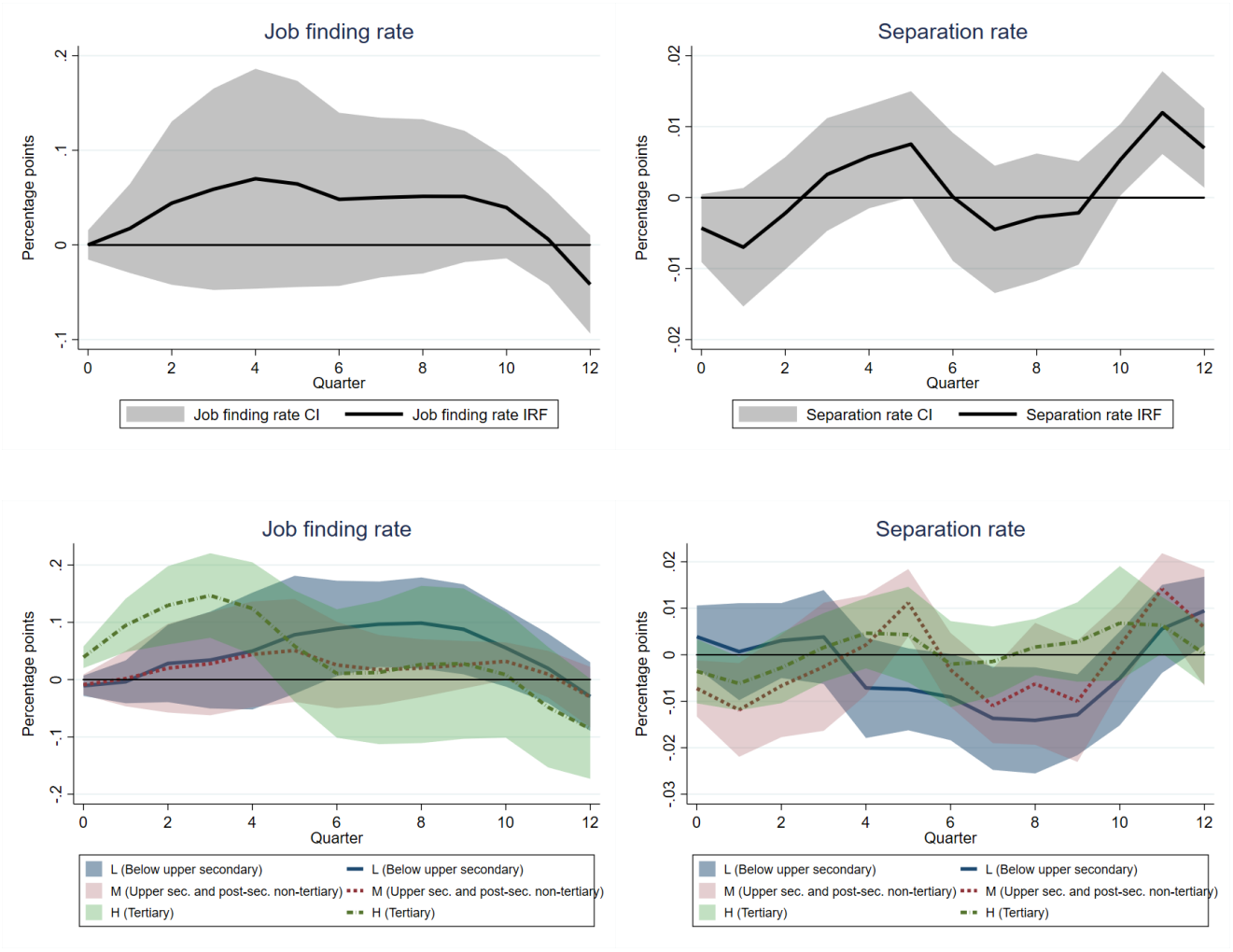
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 42: Germany



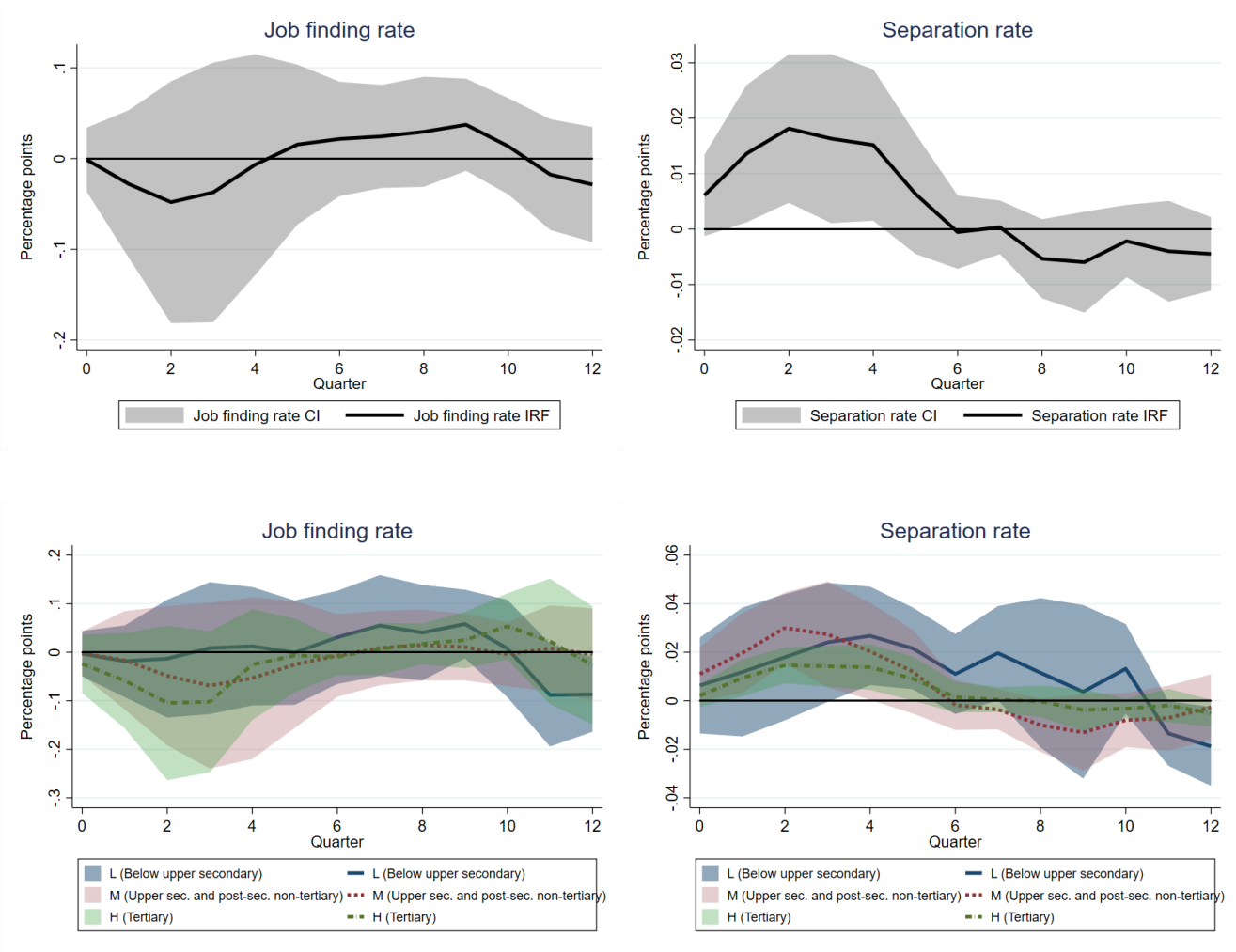
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 43: Greece



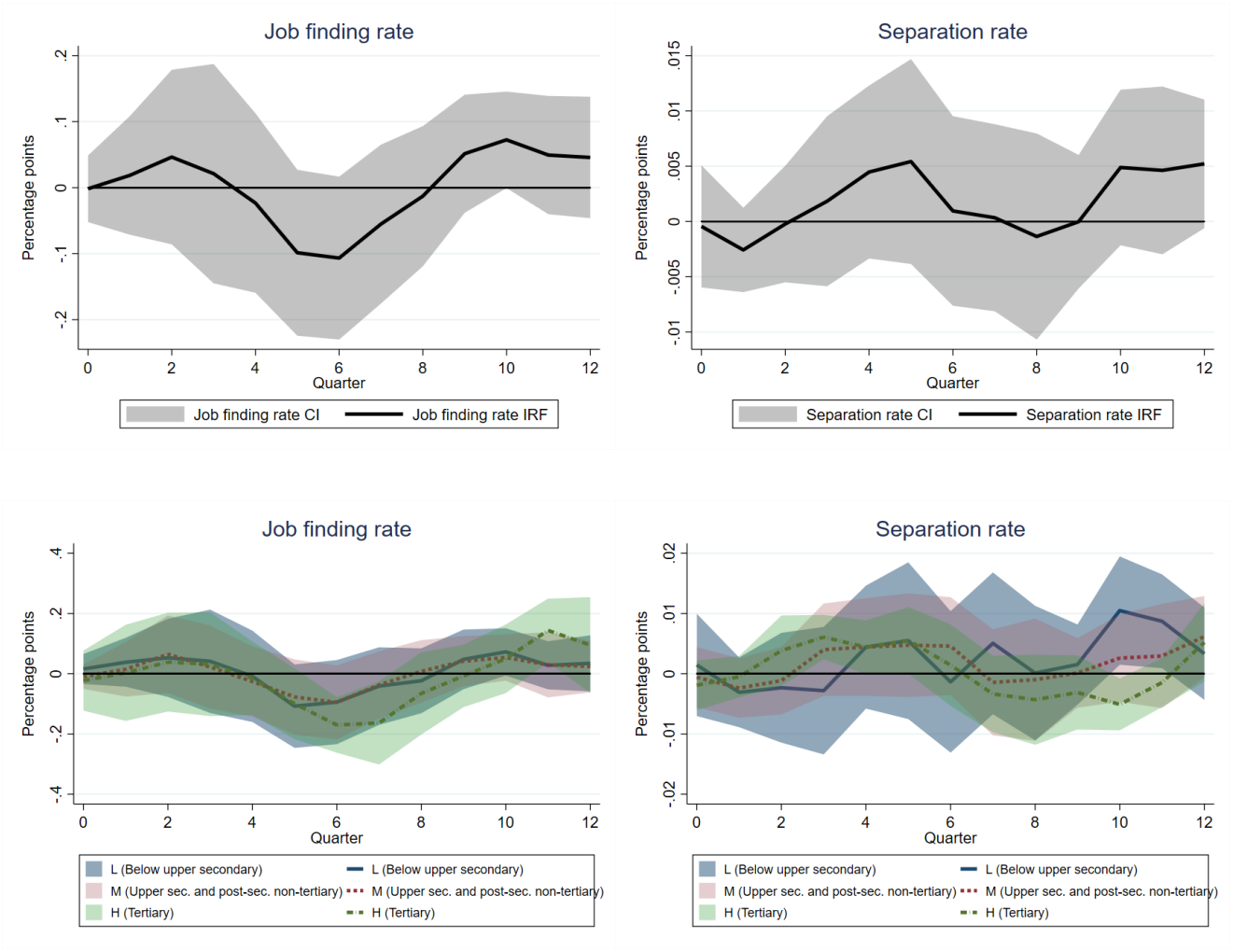
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 44: Ireland



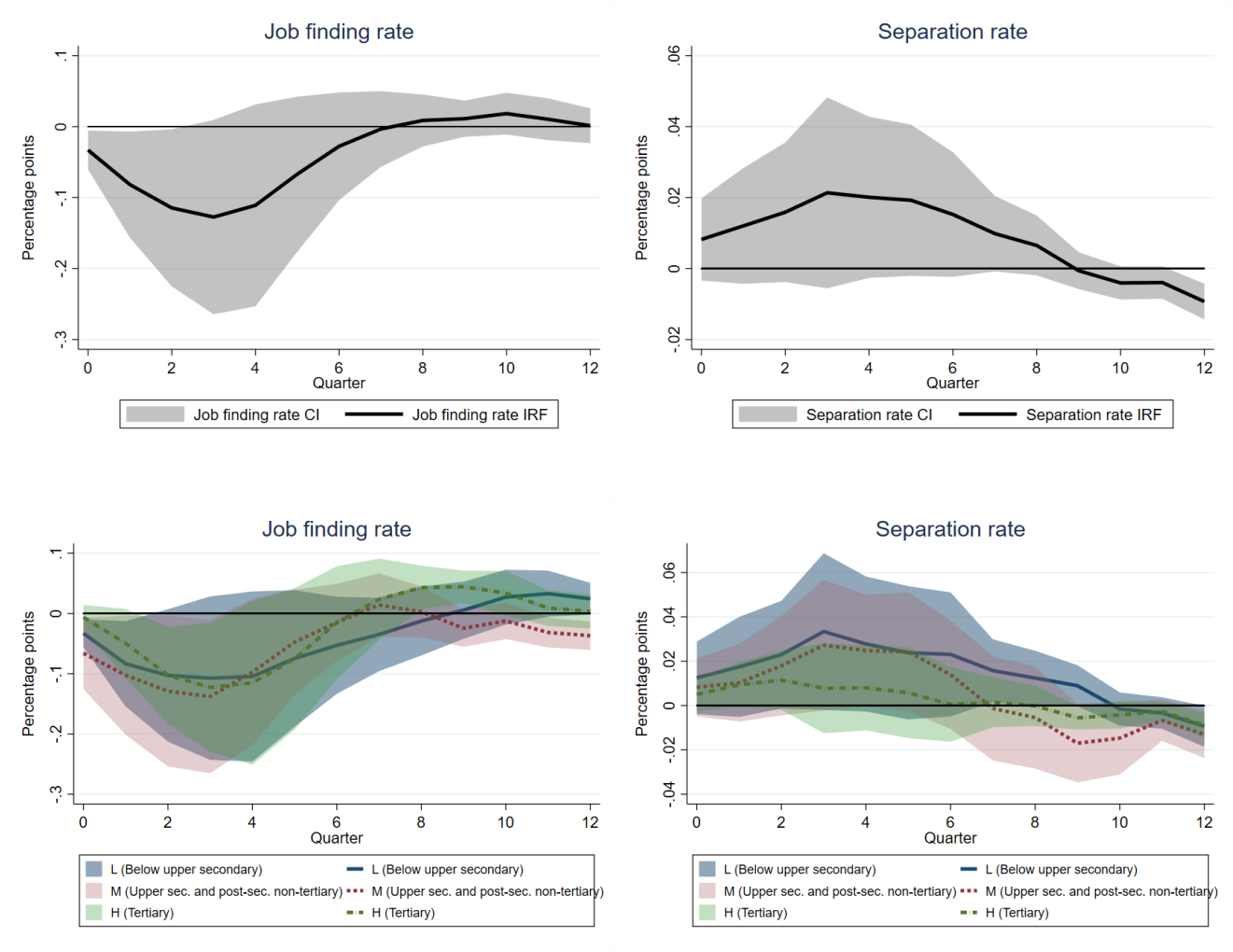
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 45: Italy



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

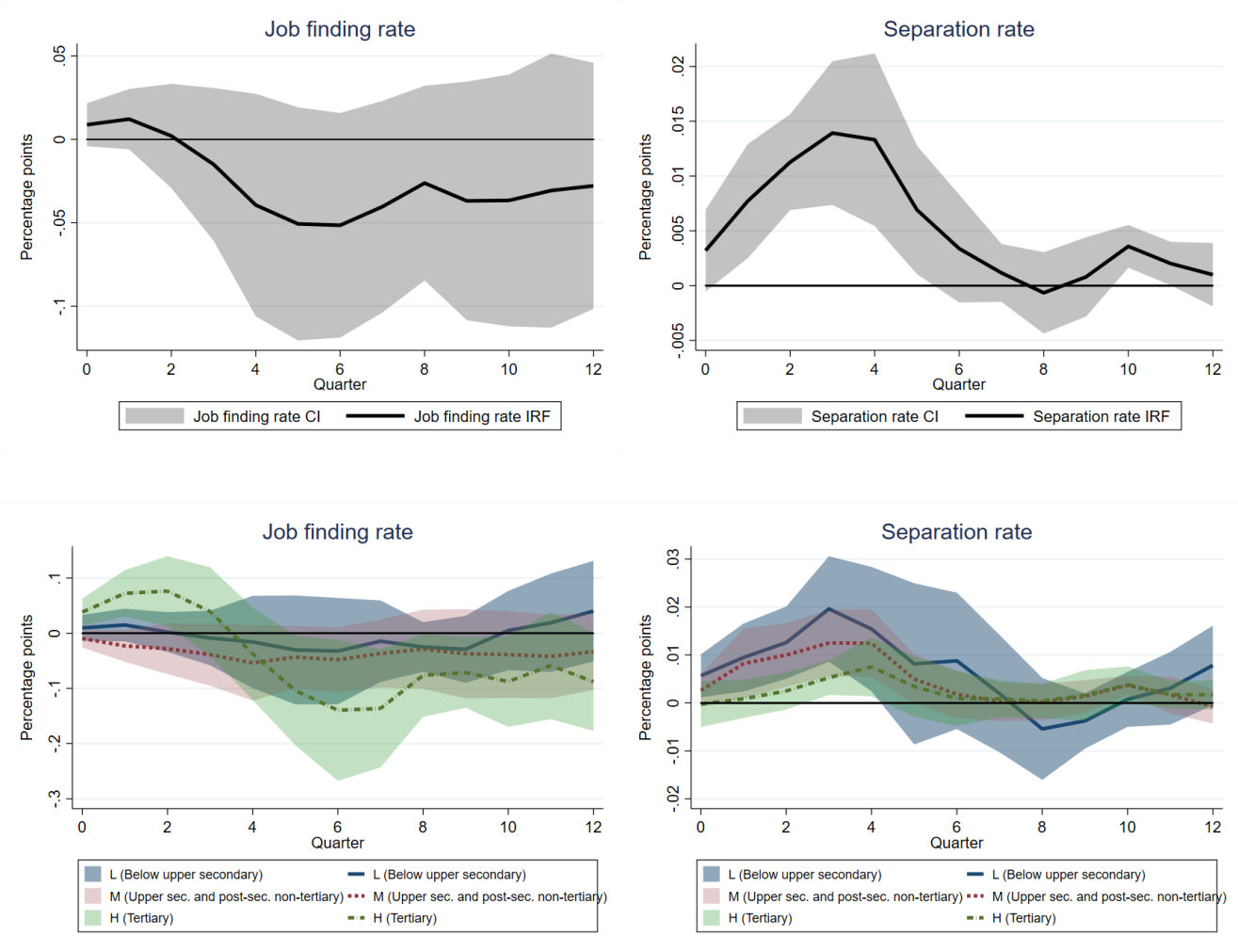
Figure 46: Spain



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

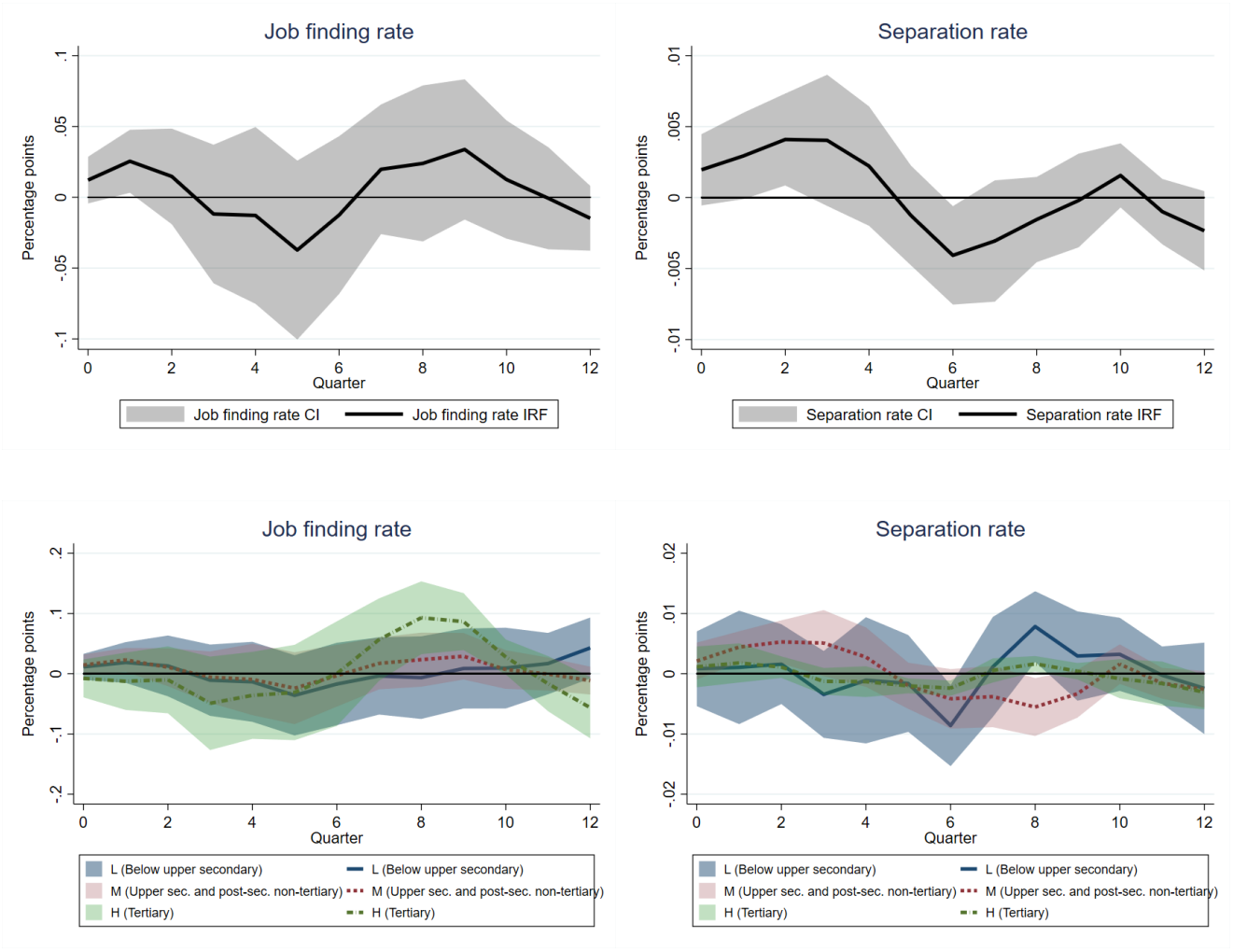
B.2.3 Unemployment duration spell less than 12 months (d<12)

Figure 47: France



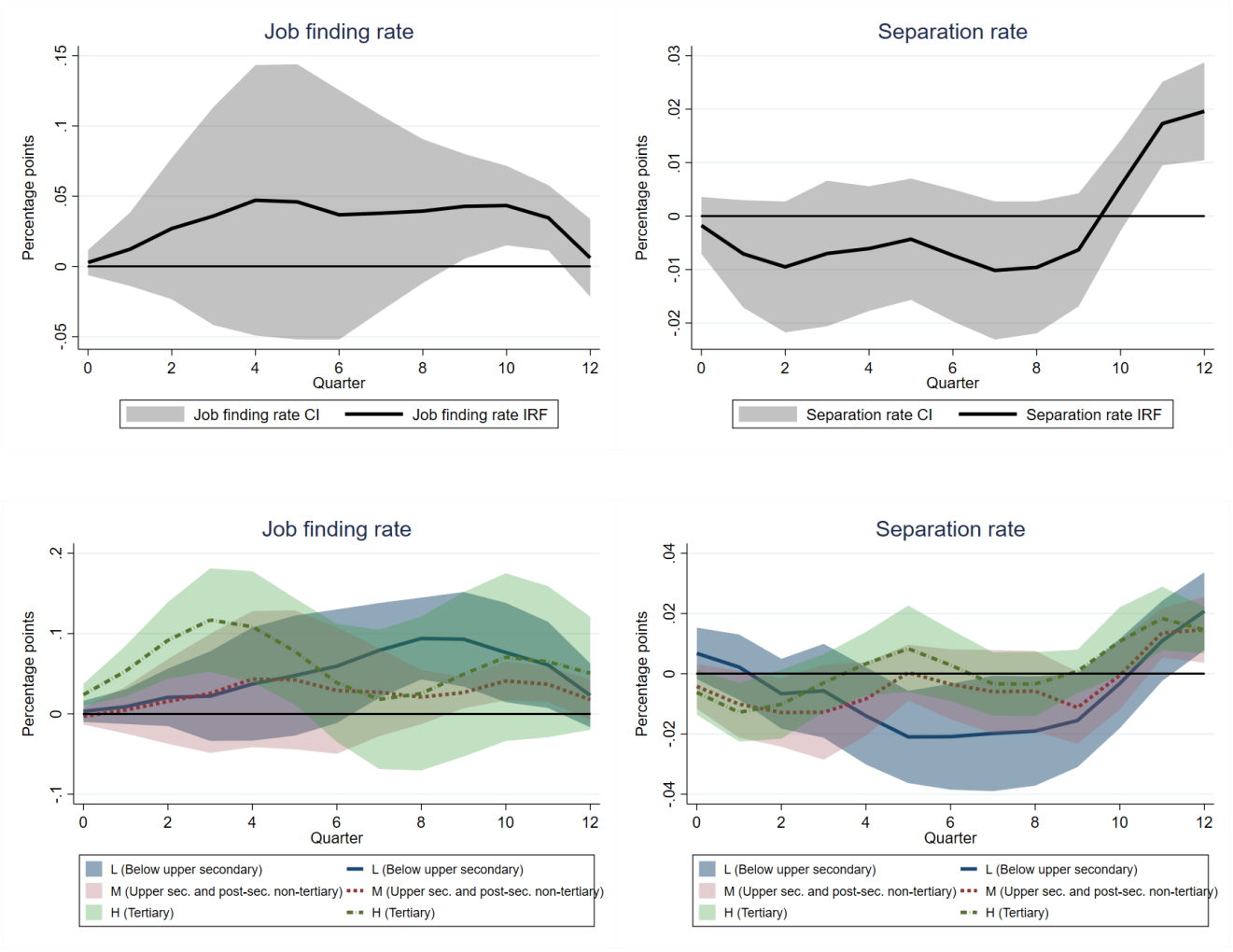
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 48: Germany



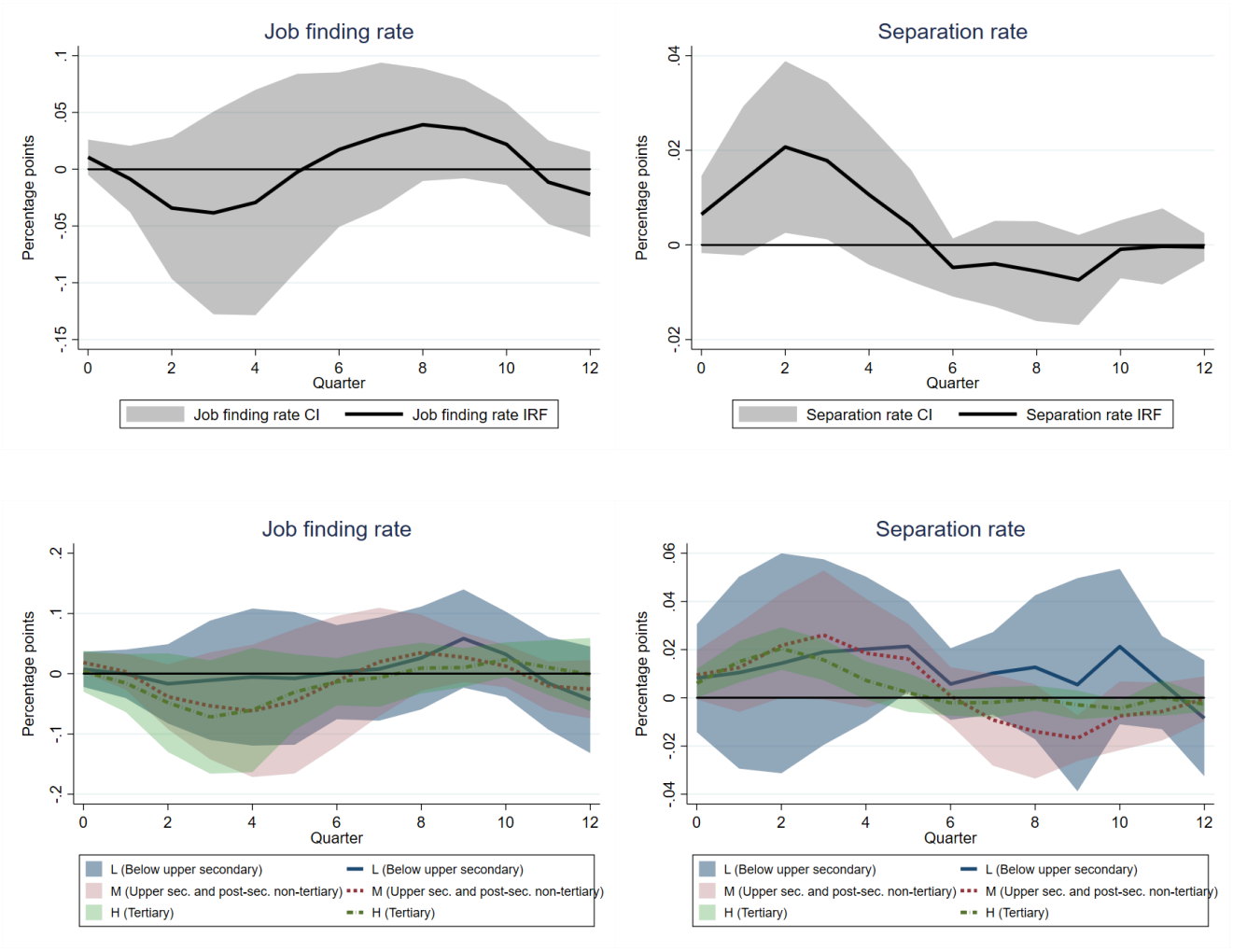
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 49: Greece



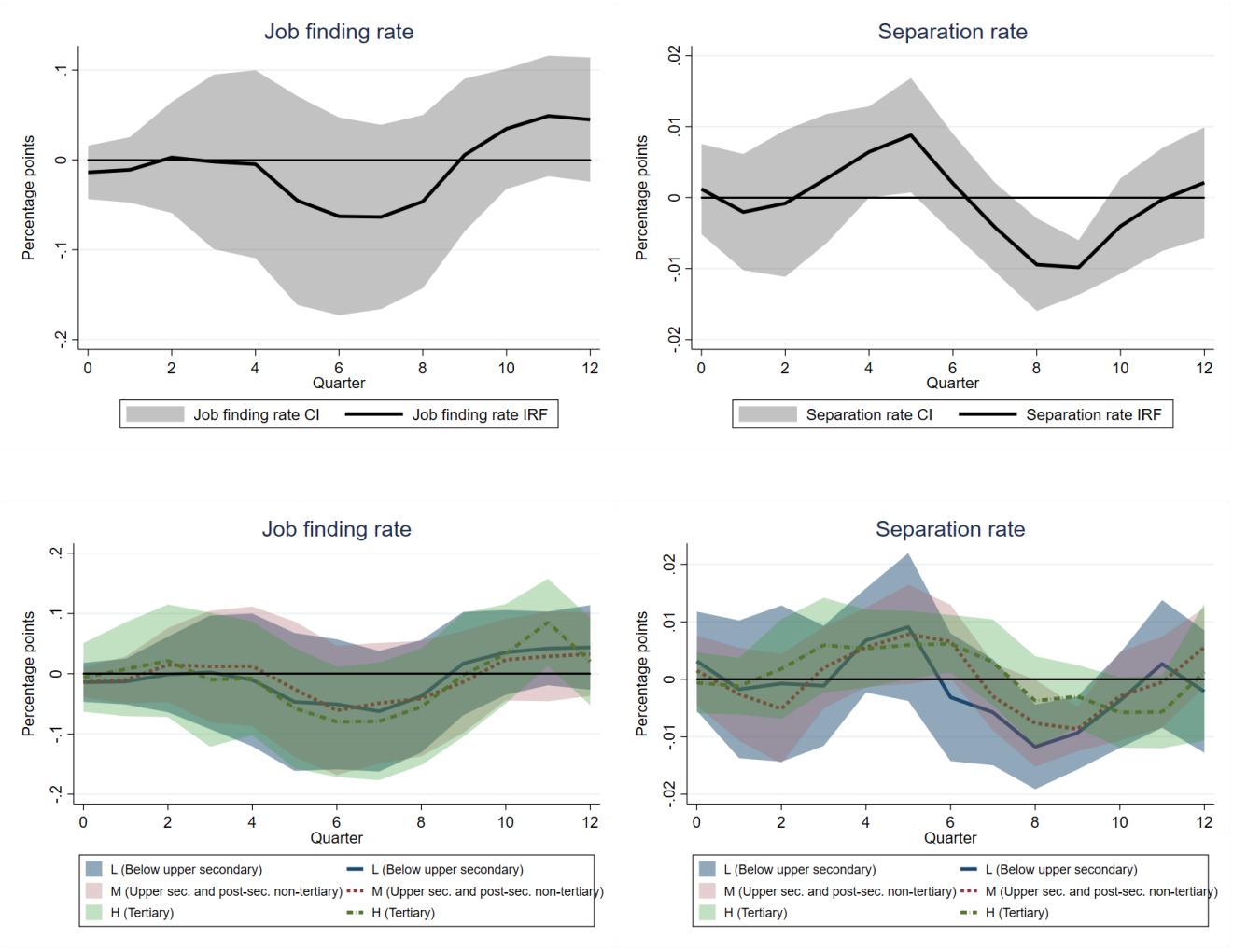
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 50: Ireland



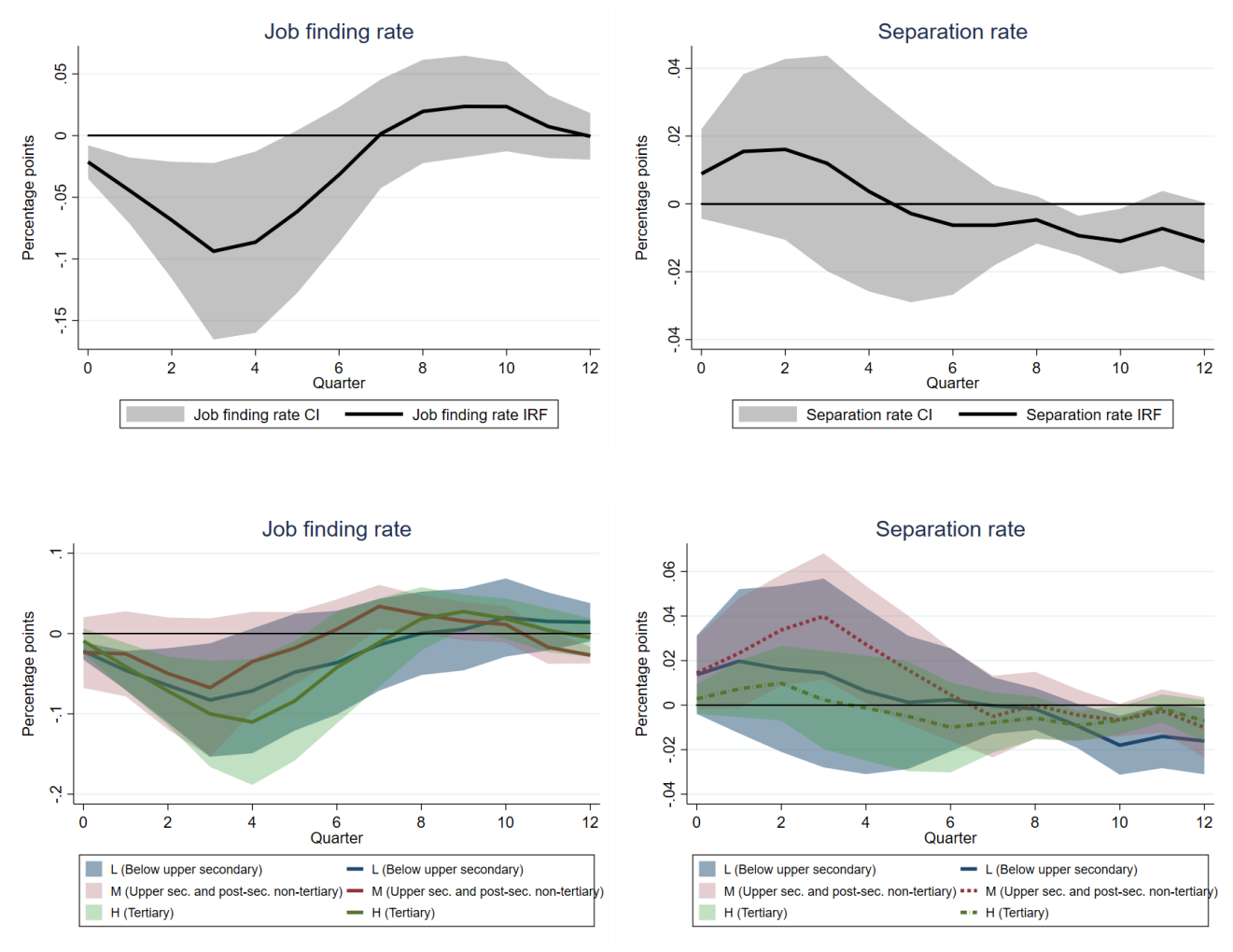
Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 51: Italy



Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure 52: Spain

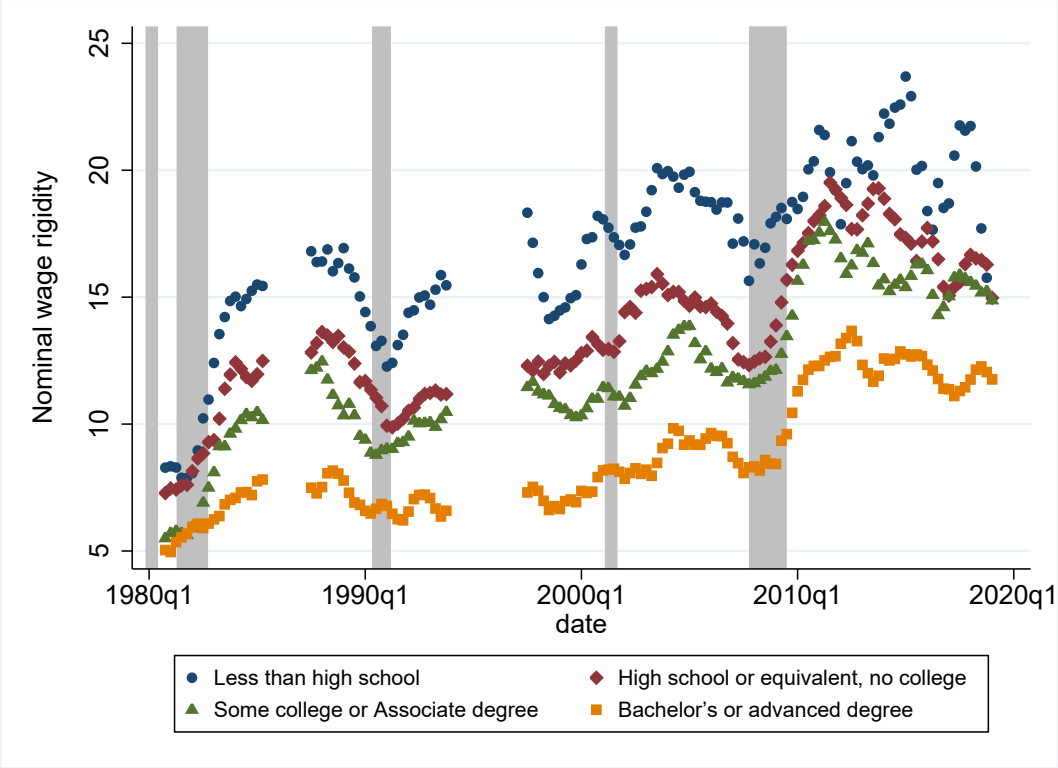


Notes: This figure shows impulse responses following a contractionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

C Additional empirical evidence from the US

C.1 Wage rigidity in the US

Figure 53: 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/

C.2 Alternative measures of a business cycle

Table 17: 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 average employment within the education group. NBER recession is a dummy variable indicating NBER recessions.

Table 18: 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.

C.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:

$$\Delta Y_{i,t} = \gamma_t + \theta_1 \, educ_i + \theta_2 \, educ_i \times \Delta lnGDP_t + \epsilon_{i,t}, \tag{39}$$

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 19: 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

D 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

$$Y_t = \left(\int_0^1 y_{j,t}^{\frac{1}{\mu}} dj \right)^{\mu} \tag{40}$$

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

$$y_{j,t} = n_{j,t}, \tag{41}$$

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

$$y_{j,t} = \left(\frac{p_{j,t}}{P_t} \right)^{\frac{\mu}{1-\mu}} Y_t, \tag{42}$$

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

$$P_t = \left(\int_0^1 p_{j,t}^{\frac{1}{1-\mu}} dj \right)^{1-\mu}. \tag{43}$$

The intermediate producer solves the following problem:

$$\max_{p_t^*, \{y_{j,s}, n_{j,s}\}_{s=t}^{\infty}} \sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} y_{j,s} - W_s n_{j,s} \right), \tag{44}$$

subject to 41 and 42. The solution to this problem is

$$\frac{p_t^*}{P_t} = \frac{\sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} \right)^{\frac{\mu}{1-\mu}} Y_s \mu W_s}{\sum_{s=t}^{\infty} \beta^{s-t} (1-\theta)^{s-t} \left(\frac{p_t^*}{P_s} \right)^{\frac{\mu}{1-\mu}} Y_s}. \tag{45}$$

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

$$\frac{B}{1+r_t} + \sum_z \Gamma^z(z) \tau_t \overline{\tau}(z) = B \tag{46}$$

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

$$1 + r_t = \frac{1 + i_t}{1 + \pi_{t+1}}. \tag{47}$$

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

$$\Gamma_{t+1}\left(\mathcal{B}, z'\right) = \int_{\{(b,z):g_t(b,z)\in\mathcal{B}\}} Pr\left(z'|z\right) d\Gamma_t(b, z), \tag{48}$$

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:

$$L_t \equiv \int z_{h,t} l_{h,t}(b, z) d\Gamma_t(b, z), \tag{49}$$

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

$$L_t = N_t. \tag{50}$$

Aggregate production is

$$N_t \equiv \int n_{j,t} dj = Y_t S_t, \tag{51}$$

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

$$S_t \equiv \int_0^1 \left(\frac{p_{j,t}}{P_t}\right) dj \tag{52}$$

with the law of motion

$$S_{t+1} = (1 - \theta) S_t (1 + \pi_{t+1})^{\frac{-\mu}{1-\mu}} + \theta \left(\frac{p^*_{t+1}}{P_{t+1}}\right)^{\frac{\mu}{1-\mu}}. \tag{53}$$

Inflation can be defined as

$$1 + \pi_t = \left(\frac{1 - \theta}{1 - \theta \left(\frac{p^*_t}{P_t}\right)^{\frac{1}{1-\mu}}}\right)^{1-\mu}. \tag{54}$$

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

$$B = \int g_t(b, z) d\Gamma_t(b, z), \tag{55}$$

$$Y_t = C_t. \tag{56}$$

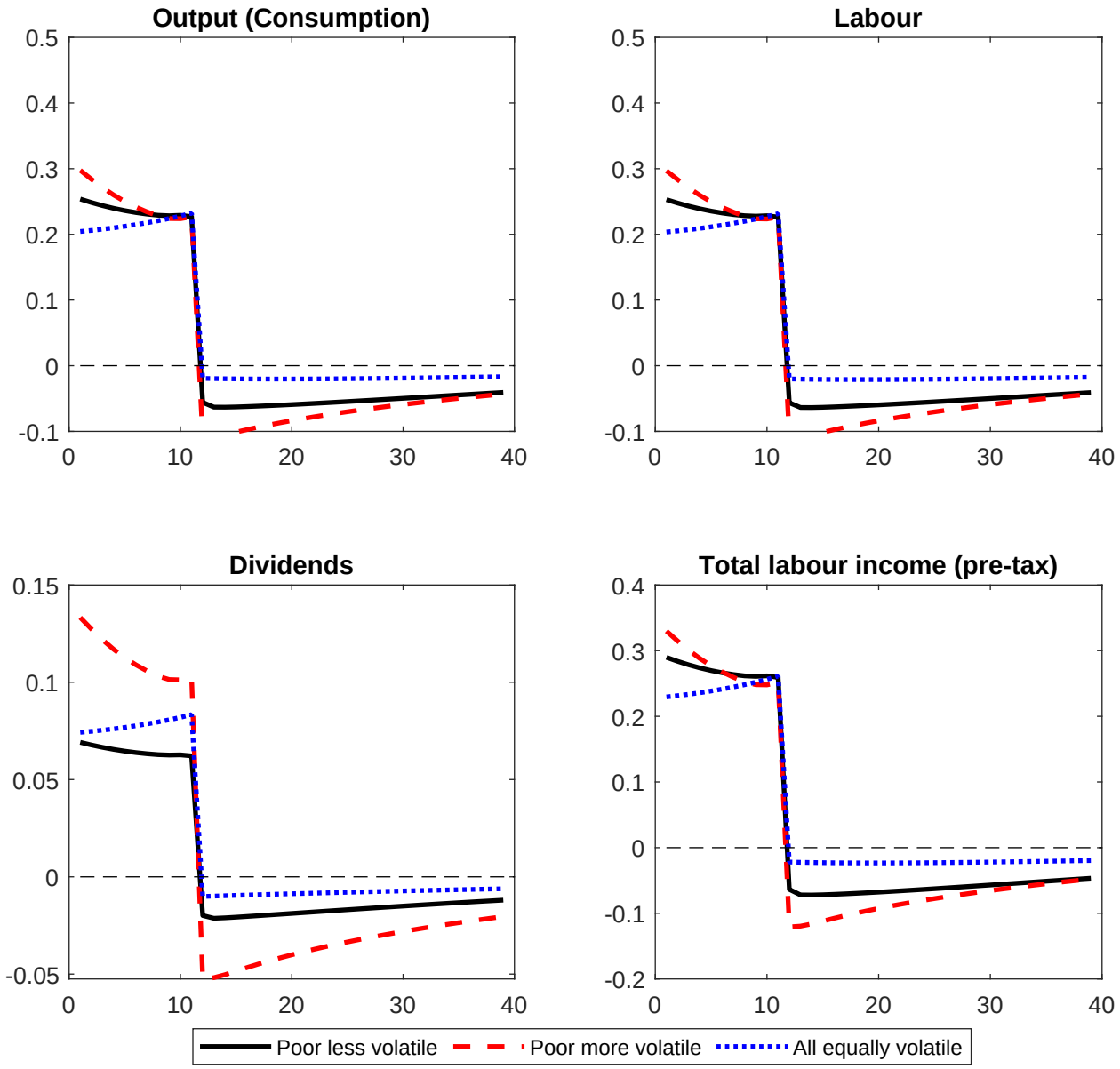
In equilibrium, all decision rules, value functions satisfy all optimality conditions, definitions, and budget constraints.

E Forward guidance and labour market volatility

E.1 European countries

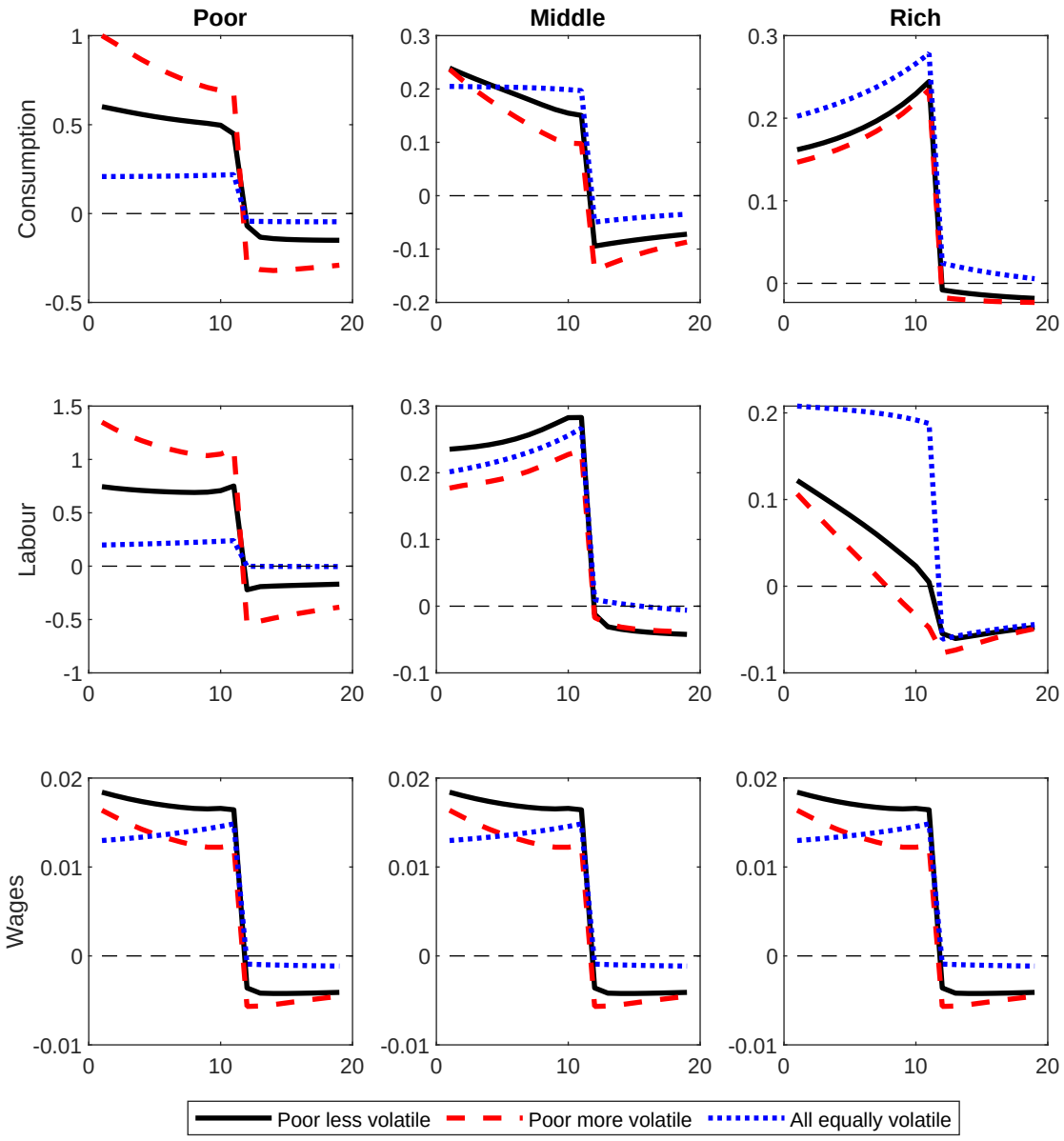
For completeness, this appendix reports the implications of higher volatility on the labour market for the poor on the effectiveness of forward guidance. We simulate forward guidance as a fully credible announcement of a one-time interest rate decrease in period 10. The results are reported in Figures 54 to 56, 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 54: Effectiveness of forward guidance depending on who gets jobs



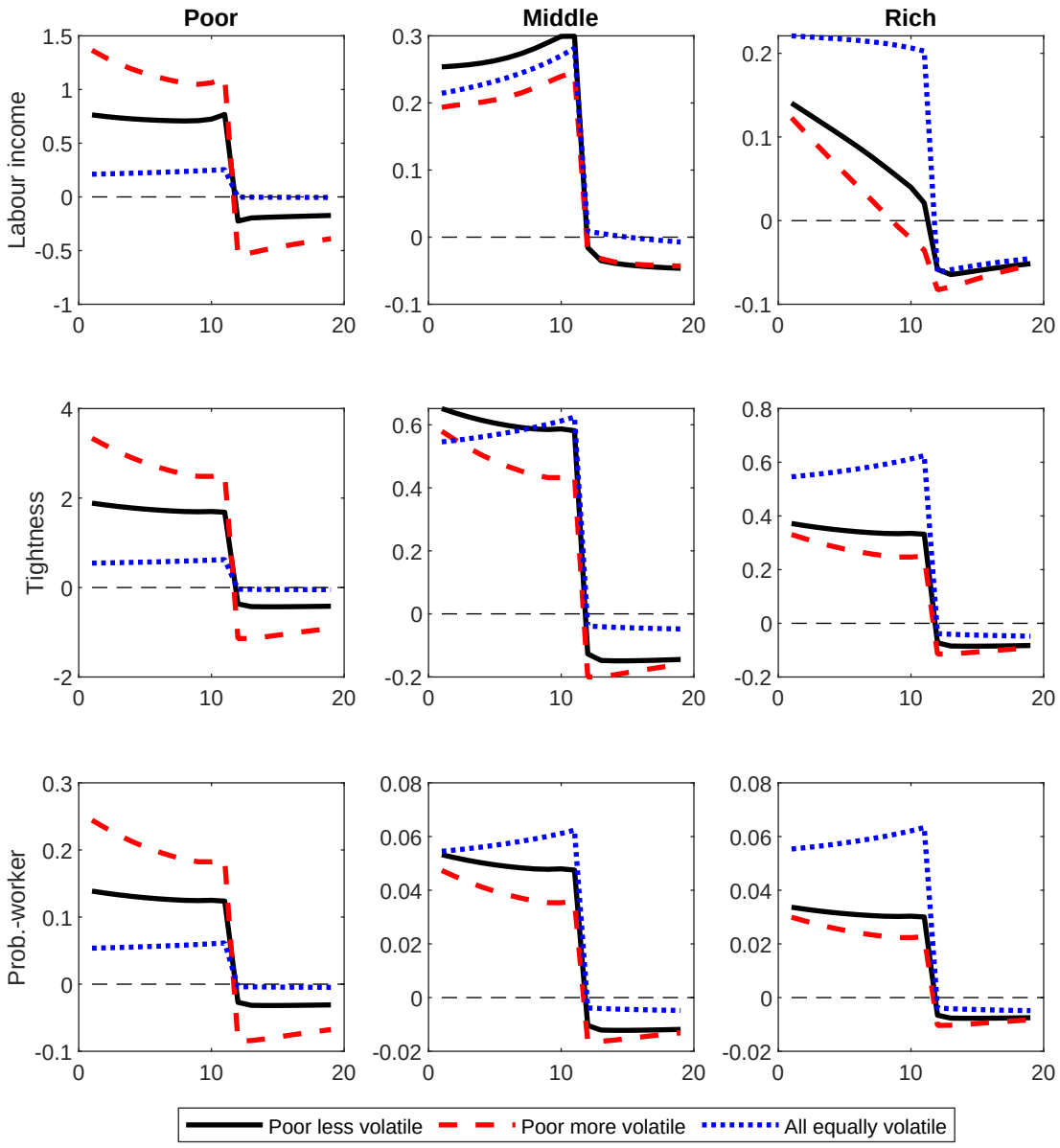
Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 55: 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 56: Effectiveness of forward guidance by groups (2)



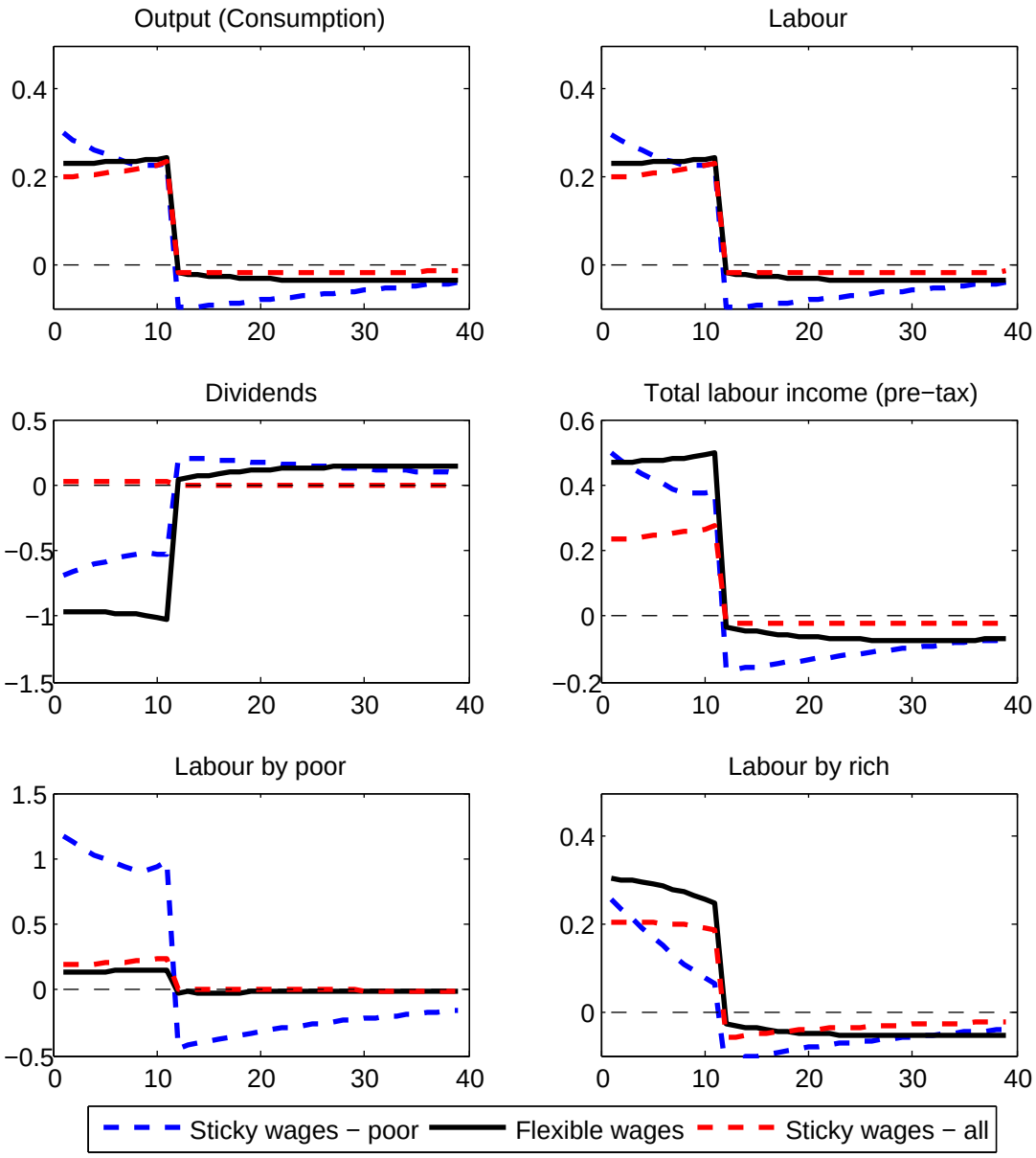
Notes: All variables are reported in percent deviations from the steady state, except probabilities, which are in percentage points. Units on the horizontal axis are quarters.

E.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 57, 58, and 59, 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

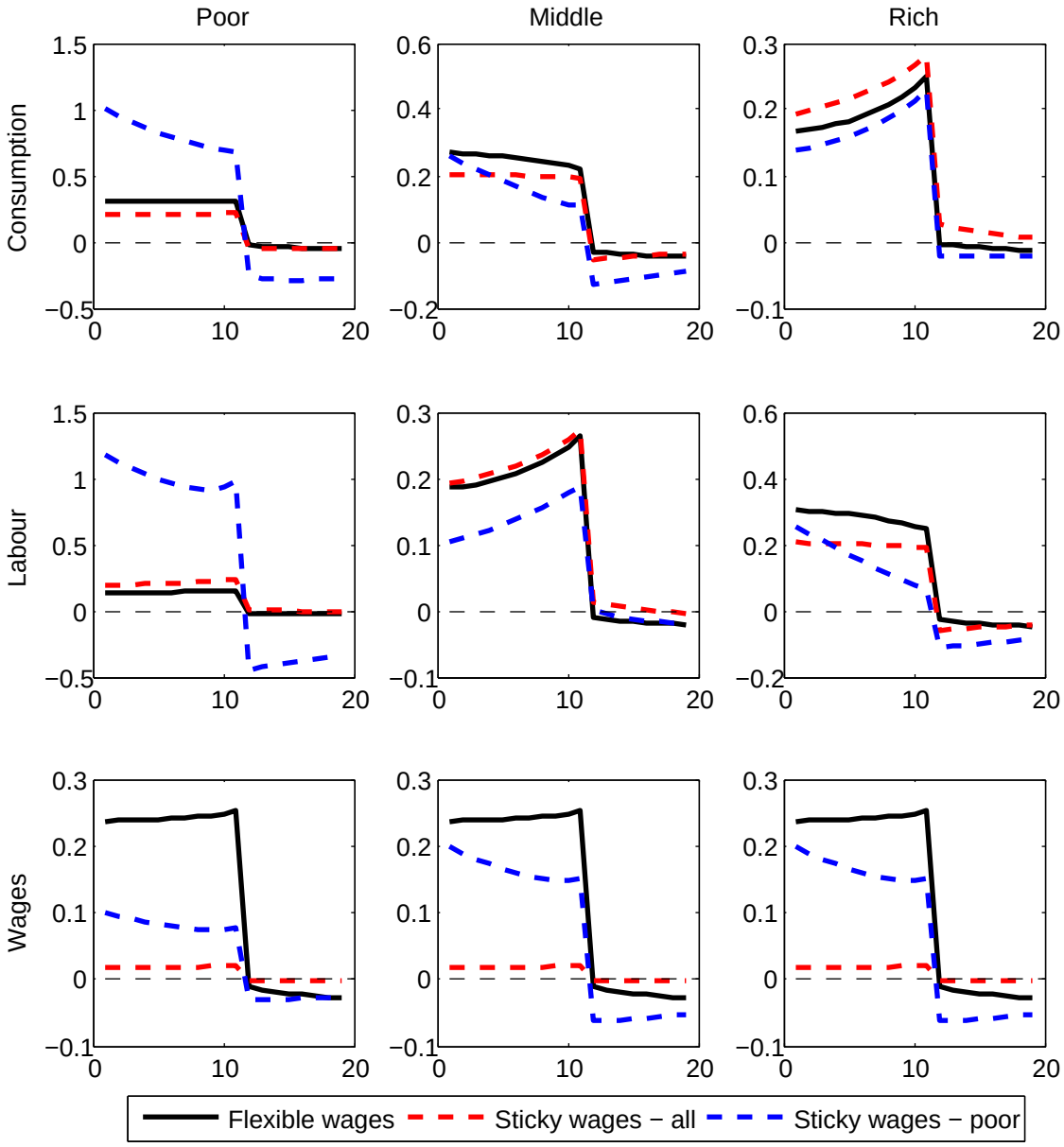
guidance only when the poor obtain jobs.

Figure 57: Forward guidance depending on who gets jobs



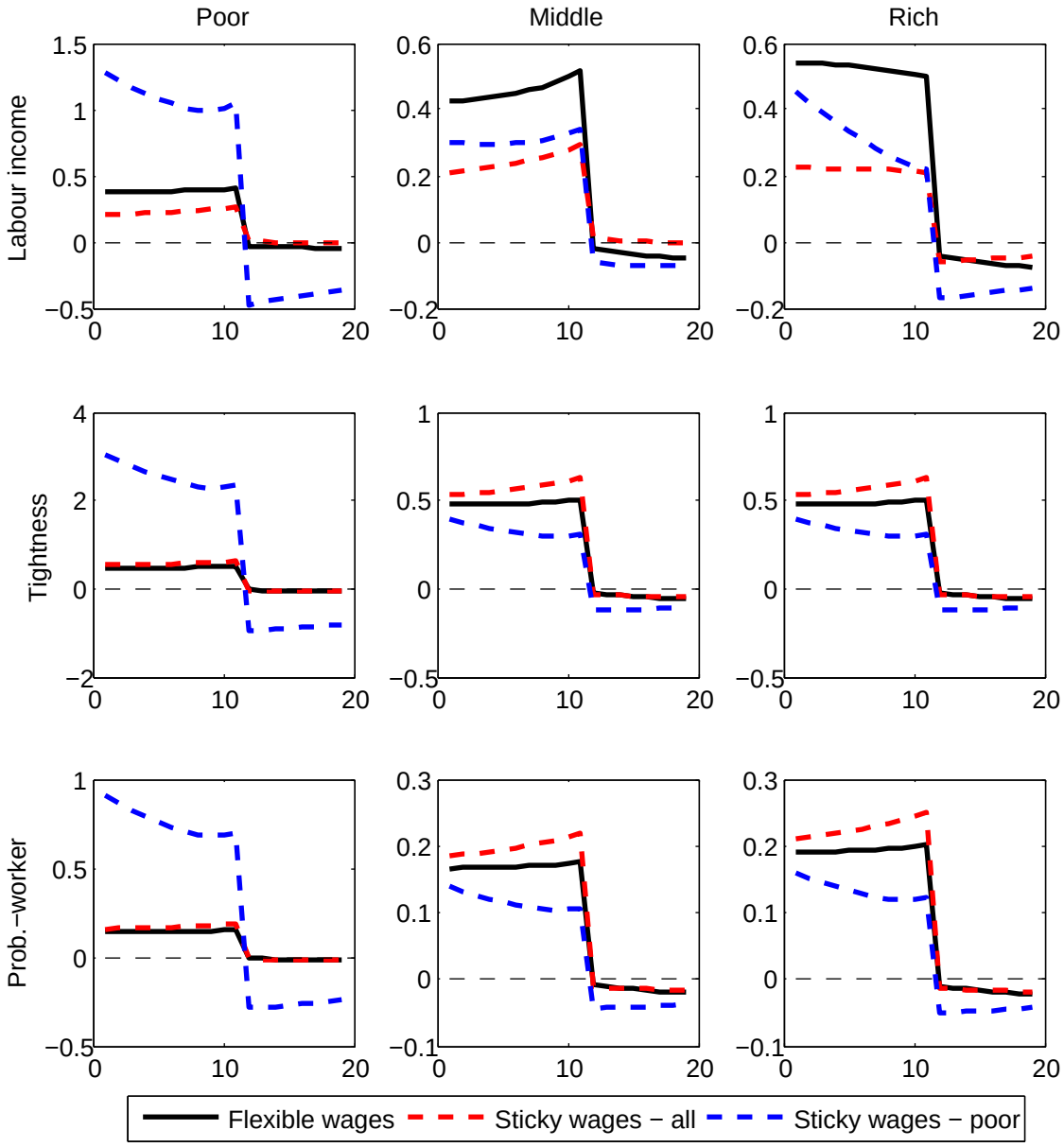
Notes: All variables are reported in percent deviations from the steady state. Units on the horizontal axis are quarters.

Figure 58: 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 59: Forward guidance, by groups (2)



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

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