Business cycle asymmetry of earnings pass-through

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Abstract

How does the firm's role as an insurance provider vary over the business cycle? Using Swedish administrative data, I document that idiosyncratic firm productivity shocks are passed through workers' earnings asymmetrically. In non-recessions, firms are good insurers against negative shocks. In downturns, they pass through a larger share of their shock. Regardless of the state of the economy, instead, positive shocks are mainly passed through when sizeable. I rationalize these findings using a directed search model of the labor market with recursive contracts. Moral hazard risk associated with on-the-job search is key to generating pass-through and the increased risk of firm disaster in recessions is necessary for matching the empirical facts. As the wage growth distribution features procyclical skewness and acyclical variance, the model also suggests a new mechanism for explaining trends in income risk variation over the business cycle. Welfare calculations reveal that workers would be willing to give up a non-negligible share of consumption to avoid this source of uncertainty.

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1 Introduction

The extent to which firms insure their workers against salary fluctuations is a long-standing question in economics (Knight, 1921), and it is based on the idea that an unequal allocation of the match's surplus uncertainty between employers and employees is desirable if they have different attitudes towards risk (Azariadis, 1975; Baily, 1974).

Increased availability of high-quality matched employer-employee data has led to greater scrutiny of this issue. In particular, recent empirical papers have found that firms shield well workers' compensations against idiosyncratic productivity shocks they are exposed to,[1] but also that the degree of insurance is not full, especially if the shocks are persistent (for a review, see Guiso and Pistaferri, 2020).

This literature has, however, predominantly focused on studying this phenomenon unconditionally of the state of the economy. There are reasons to suspect that firms' ability to insure workers might vary with aggregate shocks as, for instance, labor market and financial frictions bind differently over the business cycle. Considering that income risk is a crucial driver of individuals' decisions, taking this additional source of uncertainty into account is essential for the design of welfare-improving policies.[2]

This paper fills this gap by examining the heterogeneity in the transmission of idiosyncratic firm productivity shocks to workers' salaries over the business cycle. Specifically, I document new facts on earnings pass-through asymmetries using Swedish registry data and build a search model of the labor market to replicate these patterns, finding a key role for the increased risk of firm disaster in recessions.

More in detail, using matched employer-employee data covering the universe of non-financial private companies, employment relationships, and workers in Sweden for the period 2004-2018, I document the following facts. First, earnings pass-through of idiosyncratic firm shocks is asymmetric in the state of the business cycle.[3] Firms insure workers against negative shocks in non-recessionary periods, but they do much less so in downturns. Positive shocks, on the other hand, are shared with employees especially if sizable, and this holds regardless of the state of the economy. Compared to non-recessions, the earnings' elasticity to negative shocks in recessions

[1]Among the shocks against which a firm can insure its workers, idiosyncratic ones stand out because they can be diversified via financial markets (Pagano, 2020). The idea is that the stock market should not price idiosyncratic risk and, therefore, a firm providing insurance against them should not bear a higher cost of equity.

[2]Several papers have analyzed the effect of income risk related to the pass-through of firm shocks on workers' portfolio choices, precautionary savings, and insurance demand. For a comprehensive review, see Guiso and Pistaferri (2020).

[3]Data on hours worked are available for a limited time period and sample of firms. For this reason, I focus on earnings and from here onward I will refer to earnings and wages interchangeably.

is more than three times higher (0.020 *vs.* 0.006), even in the most conservative specification. In monetary terms, this means a reduction of approximately 1,500 SEK (in 2020 terms) in the annual salary of a worker employed at a firm experiencing a one standard deviation shock. Given that in recessions the total employment share of firms exposed to more negative shocks is around 15 percent, the aggregate implications of this phenomenon are non-negligible.

Second, negative idiosyncratic productivity shocks are on average more adverse events for the firm if they occur in downturns. In particular, the share of firms experiencing mass layoffs upon receiving these shocks in recession - defined, following von Wachter et al. (2009), as firms whose workforce shrinks by more than 30 percent in two years - is approximately 7 percentage points higher compared to the same quantity in normal times. Combined with the fact that it takes around three years from the shock for the average firm to return to positive employment growth, this indicates that negative idiosyncratic shocks have larger and more persistent effects on firms' profitability in recessions.

On the theoretical side, I rationalize these empirical patterns using a directed search model of the labor market similar to the ones used by Menzio and Shi (2010) and Balke and Lamadon (2022). Specifically, I extend the mechanism of the latter paper to an economy with business cycles. The block recursivity property of the framework allows tractability in an environment with aggregate uncertainty.

In this setting, the key elements to generating realistic pass-through are on-the-job search, workers' risk aversion, and firm commitment. In each period, currently matched firms need to deliver the worker a certain amount of utility by selecting the current wage and state-contingent contracts for the next period formulated as promised utilities which, in turn, affect on-the-job search choices. This decision entails a trade-off. On the one hand, the firm wants to insure risk-averse workers against wage fluctuations to avoid paying the volatility risk premium implied by the concavity of the utility function. On the other, not adjusting the terms of the employment contract results in waiving the opportunity to align the worker's search incentives with the firm's desire to keep the worker and sustain or end the match.

Consider a firm exposed to a persistent negative productivity shock. Since the shock reduces the expected value of the match, the firm has a lower incentive to continue the employment relationship, so it optimally diminishes the worker's share of the surplus by promising her lower utility, until this choice is balanced with the cost for the additional risk premium to be paid. This action has two consequences. First, the job-finding rate is a decreasing function of utility, so the probability that the worker is poached increases. Second, as lower promised utilities can be sustained with a diminished stream of consumption, wages are cut. The magnitude of this mechanism is amplified by a higher persistence of the shocks or a lower cost of deviating from full insurance.

In addition to the forces generating the shocks' pass-through, two key elements enable the model to match the asymmetries found in the data. The first is modeling that negative idiosyncratic firm shocks are more adverse events in recessions, which is needed to replicate the larger pass-through of these shocks in downturns. While the general equilibrium effect from a lower job finding probability in recessions pushes the framework toward the desired direction by requiring a more significant decrease in promised utility to achieve the same probability that the worker leaves, I find that it is quantitatively not strong enough to generate the asymmetries found in the data. Thus, I introduce an additional disaster state in which, upon entering, firms experience low productivity for a protracted period of time, and which I discipline using the empirical evidence on mass layoffs. As explained above, the higher the persistence of the shocks, the stronger the mechanism. Therefore, if a negative shock has a larger and more persistent effect on the expected value of the match in recessions, it will be passed through more.

The second key element is the free-entry condition, which produces a different response for positive and negative shocks. As all newly formed matches have the same initial idiosyncratic firm productivity, free-entry forces the expected value of posting a vacancy to equate its cost in equilibrium. Consequently, upon creating a new employment relationship, there is a maximum utility level that an entering firm can promise to the worker above which the match would not be viable. Because only new entrants can poach workers, any incumbent offering this value faces zero probability that the worker leaves. This restricts the pass-through but does not apply to negative shocks, thus generating asymmetry. In turn, as the incentives to retain workers for firms exposed to positive shocks are on average high enough to make them update the terms of the employment contract towards a zero poaching probability regardless of the business cycle in the used calibration, this drives down the magnitude of positive changes in promised utility and wages, and it does so in a similar fashion for recessions and non-recessions, which enables to replicate the non-state dependence for these shock.

Besides matching untargeted earnings pass-through asymmetries, the model provides a new explanation for the business cycle trends in income risk documented by a recent empirical literature (Busch et al., 2022; Guvenen et al., 2014) and confirmed also in this paper. Specifically, since the pass-through of negative shocks is on average larger in recessions and that of positive ones is acyclical, the model-generated wage growth distribution for stayers exhibits procyclical skewness and acyclical variance.

Finally, I use the model to evaluate the welfare cost of business cycles. Workers would be willing to give up a significant fraction of their consumption to avoid the effects of aggregate uncertainty in this setting, up to 2.7 percent. While this is a relatively large number compared to the estimates found by other studies (Krusell et al., 2010; Lucas, 1987), and some caution is required in interpreting this result because of non-trivial features in my framework, the lack of a saving technology in the model and the presence of firm disasters make the repercussions of wage fluctuations particularly adverse.

Relation to the literature. This paper relates to several strands of the literature. First, it contributes to the empirical research studying how workers' earnings are affected by idiosyncratic firm shocks. A seminal contribution in this area is from Guiso et al. (2005), who estimate the pass-through of persistent and transitory idiosyncratic firm shocks on stayers using matched employer-employee data from Italy. They find that workers are overall well insured: salaries are almost entirely insulated from transitory shocks and their elasticity with respect to permanent ones is very low, around 0.07. Subsequent papers have replicated their study in other countries, finding remarkably similar estimates (for a review, see Guiso and Pistaferri, 2020).[4] More recently, the increased availability of high-quality administrative data has enabled researchers to overcome some limitations related to the sample selection of stayers (Chan et al., 2020; Friedrich et al., 2019). This literature, however, has in general abstracted from business cycles. An exception is Chan et al. (2020), which is the closest contribution to this paper. Using Danish administrative data on wages, they estimate pass-through regressions to gauge the wages' elasticity to idiosyncratic firm TFP shocks. In contrast with this paper, they find that persistent negative shocks are always passed through regardless of the state of the cycle, whereas positive ones are only passed through in non-recessions. While data limitations do not allow me to check in full the effects of the diversities between their approach and mine, my paper contributes to this literature by providing results for alternative measures of workers' compensation and institutional context - earnings and Sweden, respectively - and by showing that these differences have non-trivial effects on the results. In addition, rather than reporting only the average pass-through, I document how earnings change over the whole distribution of idiosyncratic firm shocks.

Second, this study relates to the theoretical literature on employment contracts (started by Azariadis, 1975; Baily, 1974) and its application in directed search models to study labor market phenomena (e.g. Menzio and Shi, 2010, 2011; Rudanko, 2009; Schaal, 2017). In particular, it builds on recent work by Balke and Lamadon (2022), who rationalize the pass-through of firms' shocks in a framework in which the main force is firms' trade-off between insuring workers and shaping their incentives to search while on the job. I extend their mechanism to an economy with business cycles and show that adding asymmetries in the stochastic process governing firms' shocks is crucial for matching the patterns in the data.

Third, this paper is connected to studies analyzing, respectively, business cycle heterogeneity

[4] Other papers have also investigated pass-through heterogeneity in worker and firm characteristics (Juhn et al., 2018) and studied differences in the transmission of firm-level and industry-level shocks (Carlsson et al., 2016).

in the distributions of firms' productivity shocks and income shocks. Specifically, I confirm in Swedish data the finding by Salgado et al. (2020) that the skewness of firms' productivity shocks is procyclical. I also document, as do Bloom et al. (2018) and Carlsson et al. (2022), the countercyclicality of the standard deviation of these shocks for manufacturing firms. However, while I still find that volatility is slightly higher in recessions, no clear business cycle trend for it is visible in the full sample, which also includes companies operating in retail, construction, and services, as this quantity is high in some non-recessionary years too. Regarding income shocks, I document their procyclical skewness and acyclical variance in my sample, which includes only workers with stable employment relationships. This resonates nicely with the seminal contribution by Guvenen et al. (2014) who report similar trends in US administrative data and, in particular, with Busch et al. (2022) who corroborate these findings for Sweden, Germany and France and for continuously employed full-time workers.[5] In addition, since the model is able to generate these features in the wage growth distribution, my paper contributes to the part of this literature that studies explanatory mechanisms for these patterns. One of the main references in this area is Hubmer (2018), who shows that a job ladder model in a frictional labor market can also replicate the asymmetries found in the data.

Structure of the paper. The paper is structured as follows. Section 2 presents the empirical findings, Section 3 describes the model, Section 4 deals with model calibration, Section 5 presents the results obtained from the model and Section 6 concludes.

2 Empirical analysis

The empirical analysis proceeds in two steps. First, I analyze idiosyncratic firm productivity shocks. I document that negative shocks have larger and more persistent effects on the firm's profitability if they occur in recessions. Second, I examine the relationship between these shocks and workers' earnings. Specifically, I estimate a statistical model of earnings and show that residuals' log changes over the firm's TFP shock distribution exhibit different patterns in non-recessions and downturns.[6]

[5] For Spain, Arellano et al. (2021) find not only that skewness decreases in recessions but also that the variance rises.

[6] In institutional settings in which wage bargaining is highly centralized, firms have less leeway in transferring shocks to workers. Appendix B briefly describes some features of the Swedish labor market context to show that a substantial part of agreements involves firm-level bargaining.

2.1 Data

The empirical part of this paper is based on a matched employer-employee dataset created by merging information contained in three different administrative databases assembled by Statistics Sweden and accessed through the servers of the Institute for Evaluation of Labor Market and Education Policy (IFAU), in Swedish *Institutet För Arbetsmarknads-och Utbildningspolitisk Utvärdering*.

The first is the Structural Business Statistics (SBS) dataset, which mainly contains balance sheet and accounting information for the universe of non-financial corporations in Sweden starting from 1997. From this dataset, in addition to balance sheet items, I recover a value-added measure constructed by Statistics Sweden and information on the operating sector of each firm.

The second source is the Register-Based Labour Market Statistics (RAMS) dataset, which contains information on the universe of employment relationships in Sweden from 1985 onward. On the firm's side, I collect information on the type of legal entity and the municipality where the company is located. On the workers' side, I gather information on salaries, length of working relations, and the worker's occupational status (employee, self-employed, etc.). Then, I classify a worker as employed if she is working at least six months in a year, and I assign each employed worker a unique working place each year as the firm where she gets the highest salary. Based on this, I construct an annualized salary measure when a worker stays at the firm for less than a full year and compute firm-level total employment.

The last dataset is the Longitudinal Database on Education, Income and Employment (LOUISE), which contains information on the socio-economic and demographic status of the Swedish population from 1985 onward. From this source, I recover information on civil status, gender, year of birth, number of children, and education.

Sample restrictions. The time period of the analysis is 2004-2018.[7] On the firm side, I restrict the sample to firms with at least five employees, with positive value-added, wage bill, total fixed assets, and equity, whose juridic form is limited liability company, and operating in manufacturing, construction, retail, and services sectors. On the worker side, I consider individuals between 20 and 60 years old whose occupational status is employee. To limit the impact of outliers, I exclude workers in the bottom 5 percent of the distribution of real[8] annual earnings (around 55,000 SEK) and firms in the bottom 0.5 percent of the distributions of value-added (around 515,000 SEK) and wage bill (around 465,000 SEK). Appendix B contains

[7] In 2003, the value-added measure in my data is not reliable for construction and services. The last year in the merged dataset is 2018.

[8] Throughout the paper the reference year for variables in real terms is 2020.

more information on the data.

Sample description. Figure 1 shows sample coverage over time. The number of firms included is around fifty thousand each year, and the number of workers is about 1.5 million at the beginning and gradually increases roughly to 1.8 million. As visible from the first two rows, the Great Recession had a significant impact on the Swedish economy between 2009 and 2010.

Looking at different sectors, Figure 1 reveals that about one-third of the firms operate in services, followed - in decreasing order - by retail, manufacturing, and construction. A similar pattern holds on the workers' side, with the difference that manufacturing employs more people than retail. In terms of size, more than two-thirds of the firms are small. Medium-size firms (20-49 employees) come second, followed by large (50-99) and very large firms (100 or more). Despite being few, the latter group employs a substantial part of workers - about two-thirds, followed by small, medium, and large companies.

The bottom part of Figure 1 considers sample coverage in terms of total value-added and employment in manufacturing, construction, retail, and services, computed from national accounts.[9] [10] In all years, the sample covers around 65 percent of value-added and employment. Manufacturing and services constitute the main bulk, followed by retail and construction. When looking at size, the largest share for both value-added and employment is made of very large firms followed, in decreasing order, by small, medium, and large companies. Overall, the sample provides good coverage of the sectors considered.

Tables 1 and 2 present some summary statistics for workers and firms computed pooling across all the years in the sample. Overall, there are almost 4 million unique workers, 26 million worker-year observations, and about 130 thousand unique firms and 800 thousand firm-year observations.

[9] Appendix B describes the sources used for aggregate data.

[10] Figure A.1 provides the same shares as a fraction of totals for the non-financial private sector and the whole economy.

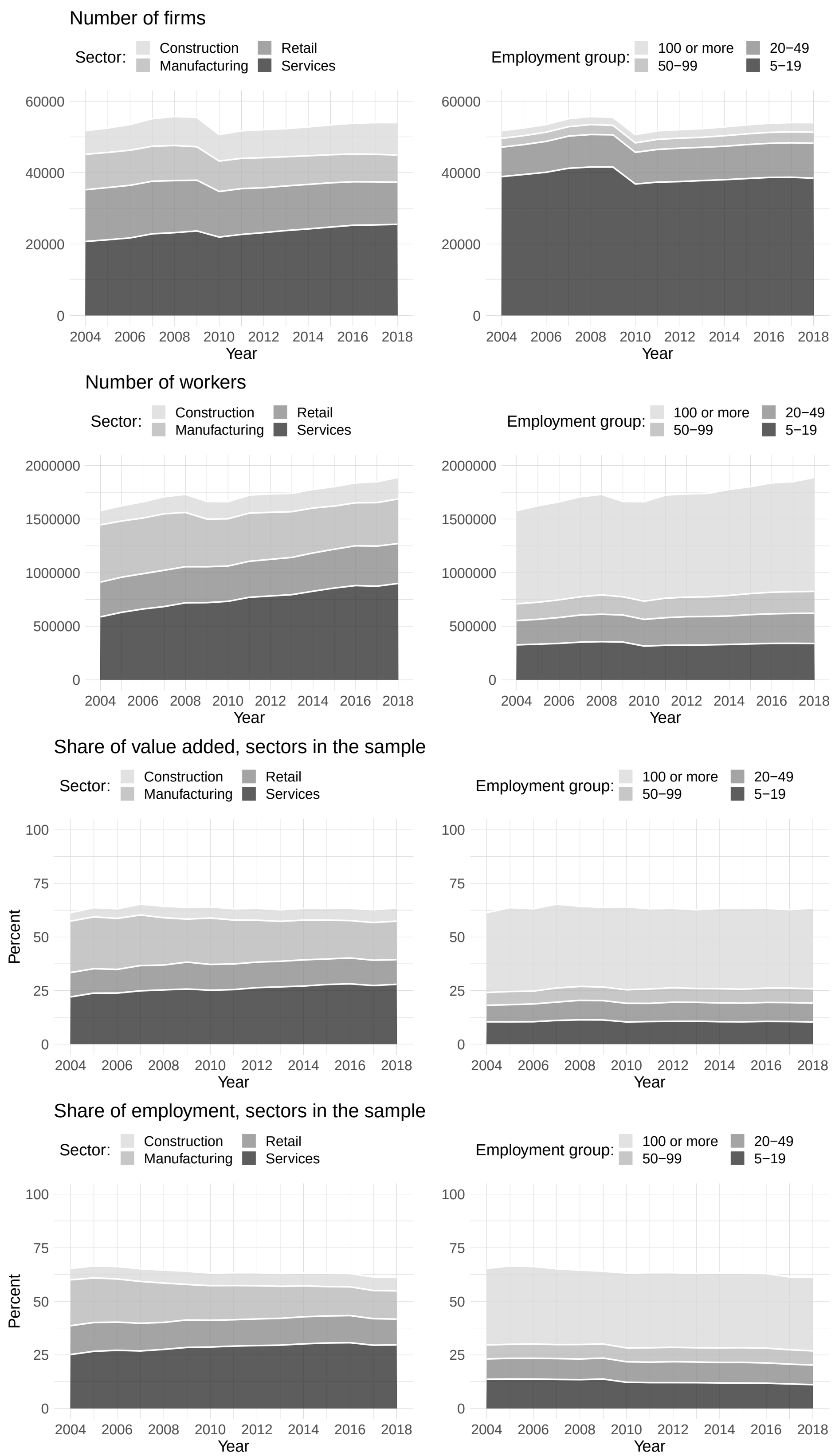

Figure 1: Sample coverage by sector and employment group. The third and fourth rows depict, respectively, the share of aggregate value-added and employment in the sectors in the sample (manufacturing, construction, retail, services).

Considering workers first, Table 1 reveals that the average worker in the sample is around forty years old, has a 0.55 probability of having children, and has about two kids, conditional on having any. Roughly one-third of the workers are married. The same proportion has more than a high school diploma. On average, workers stay about six years at the same firm, but there is sizable variability. Males are over-represented, being just less than two-thirds.

The average salary is about 370 thousand SEK, but there is considerable heterogeneity, as the standard deviation is just below the same number. Average earnings are increasing in firm size, except for very large firms in retail and services. Conditional on working in small and medium-sized firms, the average salary is similar across sectors. Workers at large or very large construction firms or at very large manufacturing companies get paid relatively more. Earnings' heterogeneity, in general, also increases in firm size and is highest in services and lowest in construction.

	Employment group				
	5-19	20-49	50-99	100+	All
I. Manufacturing					
Earnings	331,672	356,344	379,223	429,605	404,865
	(211,802)	(222,773)	(262,543)	(337,988)	(309,148)
II. Construction					
Earnings	335,381	374,057	408,851	439,798	388,421
	(128,985)	(149,863)	(231,959)	(224,314)	(188,520)
III. Retail					
Earnings	324,741	370,029	374,333	347,059	348,145
	(213,866)	(292,625)	(303,479)	(315,919)	(288,843)
IV. Services					
Earnings	335,250	363,043	374,706	364,981	360,175
	(292,137)	(304,042)	(303,493)	(332,365)	(318,283)
I. All					
Earnings	332,019	364,701	378,712	387,277	372,315
	(239,902)	(269,209)	(287,816)	(327,419)	(300,525)
Age	38.9	(11.2)			
Share with children	0.55				
Number of children, conditional	1.8	(0.8)			
Share married	0.36				
Share with more than high school	0.33				
Tenure, years	6.1	(5.8)			
Share females	0.36				
Unique workers	3,970,335				
Worker-year observations	25,986,135				

Table 1: Summary statistics for workers, 2004-2018. St. dev. in parenthesis. Monetary values in 2020 SEK.

On the firm side, Table 2 shows that the value-added per worker for the average firm in the sample is about 760 thousand SEK, and its growth rate is 3.5 percent. However, as depicted by the standard deviations, there is substantial heterogeneity. Value-added per worker is increasing in firm size. Its growth rate is, instead, decreasing overall. The services sector has the highest variability in value-added per worker, and construction has the lowest.

	Employment group				
	5-19	20-49	50-99	100+	All
I. Manufacturing					
VA/worker	731,738	791,437	918,059	1,077,034	787,303
	(842,344)	(1,809,483)	(2,397,940)	(1,937,792)	(1,379,942)
VA/worker, log growth	0.036	0.014	0.009	0.006	0.026
	(0.341)	(0.323)	(0.361)	(0.346)	(0.339)
II. Construction					
VA/worker	705,033	731,824	785,255	808,999	713,242
	(543,921)	(408,260)	(323,921)	(297,303)	(516,778)
VA/worker, log growth	0.052	0.020	0.019	−0.004	0.044
	(0.313)	(0.287)	(0.290)	(0.327)	(0.308)
III. Retail					
VA/worker	707,867	828,028	843,325	885,480	737,479
	(708,197)	(805,108)	(886,850)	(1,219,887)	(756,142)
VA/worker, log growth	0.032	0.006	0.004	0.000	0.025
	(0.348)	(0.347)	(0.365)	(0.341)	(0.349)
IV. Services					
VA/worker	768,086	776,289	815,412	870,022	776,861
	(1,867,334)	(1,256,015)	(1,246,819)	(2,324,583)	(1,773,234)
VA/worker, log growth	0.053	0.014	0.019	0.006	0.040
	(0.370)	(0.345)	(0.342)	(0.320)	(0.361)
V. All					
VA/worker	736,856	784,384	844,613	932,135	759,328
	(1,340,623)	(1,232,919)	(1,530,771)	(1,974,596)	(1,368,924)
VA/worker, log growth	0.045	0.013	0.013	0.004	0.035
	(0.351)	(0.334)	(0.348)	(0.332)	(0.347)
Unique firms	129,500				
Firm-year obs.	798,610				

Table 2: Summary statistics for firms, 2004-2018. St. dev. in parenthesis. Monetary values in 2020 SEK.

2.2 Recessionary and non-recessionary episodes

Figure 2 plots the growth rate of real GDP and the unemployment rate in Sweden.[11] GDP growth was negative just in three years, 2008, 2009, and 2012. Lagged unemployment rose in the aftermath of the Great Recession, decreased afterward, and then slightly rose again during

[11] See Appendix B for more details on the data.

the European debt crisis. Growth slowed down - but was still positive - from 2016 until the end of the sample. During the same period, unemployment gradually decreased.

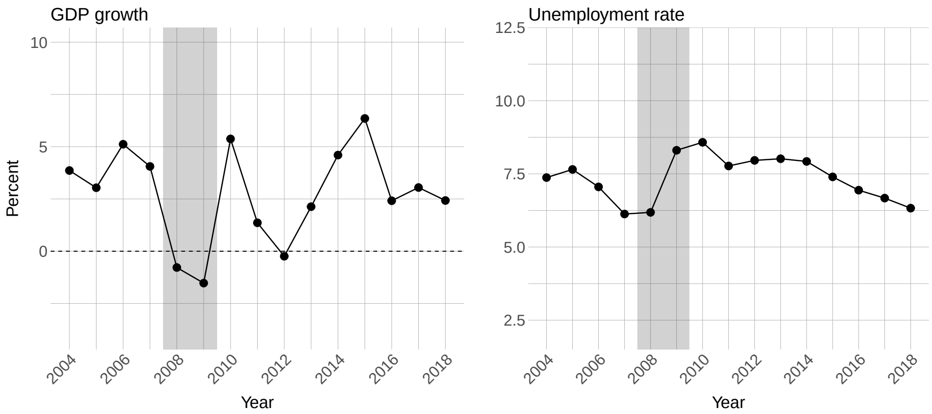

Figure 2: GDP growth and unemployment in Sweden. Shaded area corresponds to recessionary years.

Based on these graphs, I define recessions (R) the years 2008-2009 and non-recessions (NR) the remaining years. I do not include 2012 because lagged unemployment did not rise significantly in that episode. As described in Appendix C.1, I have also experimented with alternative definitions.

2.3 Idiosyncratic firm shocks

Following Friedrich et al. (2019), I use the logarithm of value-added per worker as measure of productivity.[12] I denote this variable for firm j at time t with z_{jt}. Then, as in Bloom et al. (2018), I estimate the following model:

$$z_{jt} = \rho z_{jt-1} + \lambda_t + \mu_j + \nu_{jt} \tag{1}$$

where λ_t are time fixed effects, μ_j firm fixed effects, and ν_{jt} the residual, which is the measure of idiosyncratic TFP shock.[13]

To better understand the properties of the shocks over the business cycle, Figure 3 plots their cross-sectional standard deviation, Kelly's skewness over time, and the difference between the

[12] I have also experimented using the residual from the decomposition of a Cobb-Douglas production function including both labor and capital. As shown in Appendix C.2, results are robust to this alternative definition.

[13] I acknowledge - like Bloom et al. (2018) - that this measure potentially includes shocks other than pure TFP ones. Two elements, nevertheless, are reassuring that it is a good proxy for them. First, as explained in footnote 12, results are robust when controlling for capital. Second, while I do not have information on prices and capacity utilization at the firm level, a recent paper by Carlsson et al. (2022) focusing on the Swedish manufacturing sector, finds that controlling for these two factors when constructing productivity results in TFP shocks with similar properties to the ones obtained when not doing that. Specifically concerning prices, the authors find a limited impact because they do not change much following pure TFP or demand shocks.

cumulative density function in recessions and non-recessions. Even if the magnitudes are not as large as previously found by the literature (Bloom et al., 2018; Carlsson et al., 2022; Salgado et al., 2020), it is evident in the pictures that the Great Recession was a period of higher uncertainty and of increased risk of being exposed to negative shocks. However, unlike the above-mentioned studies, Figure 3 does not support a clear countercyclical business cycle trend in the standard deviation of the shocks in my sample.[14]

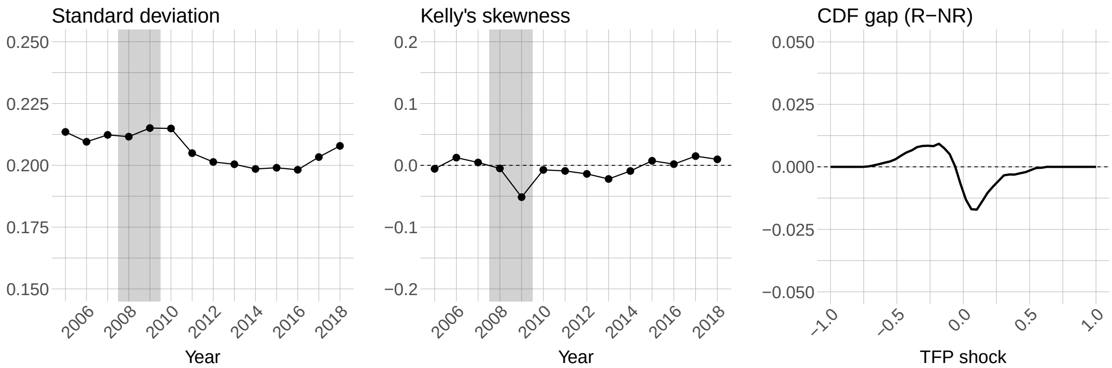

Figure 3: Measures of cross-sectional dispersion of idiosyncratic firm TFP shocks over time and CDF difference between recessions and non-recessions.

Figure 4 takes a closer look at business cycle asymmetries in the impact of idiosyncratic shocks on firms' performance by reporting the difference in the share of firms experiencing mass layoffs[15] between recessions and non-recessions over the distribution of TFP shocks.[16]

[14]Results available upon request show, instead, that the standard deviation of the shocks is countercyclical when restricting the sample to manufacturing firms.

[15]Following von Wachter et al. (2009), I define a mass layoff as a reduction of more than 30 percent of the workforce in the two years following the shock.

[16]Figure A.2 in the Appendix reports the shares for recessions and non-recessions in levels.

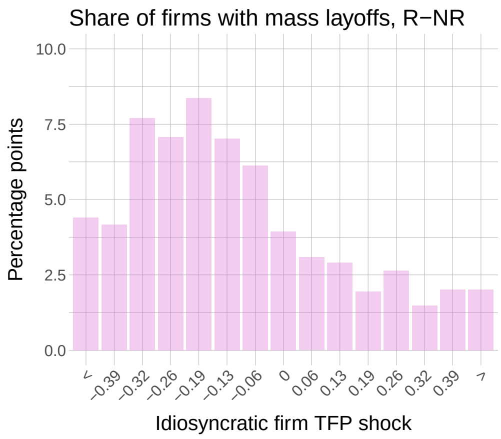

Figure 4: Difference in the share of firms experiencing mass layoffs over the distribution of idiosyncratic firm TFP shocks between recessions and non-recessions. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

Compared to those exposed to positive ones, firms experiencing negative shocks in recessions are more likely to face mass layoffs. Under the assumption that mass layoffs are good proxies for long-lasting unfavorable circumstances (it takes on average 2.8 years for a firm experiencing a mass layoff after a negative shock in recession to return to positive employment growth), the graph provides evidence that negative idiosyncratic firm shocks are more disastrous events if they occur in recessions.

2.4 Workers' earnings

To recover the part of the change in salary not due to observables, I use a statistical model of worker earnings. Let w_{ijt} indicate log earnings of individual i employed at firm j in period t. I assume that w_{ijt} can be modelled with the following linear specification:

$$w_{ijt} = X'_{ijt}\phi + \omega_{ijt} \tag{2}$$

The matrix of control variables X_{ijt} includes worker- and firm-specific characteristics and information related to each employment relationship. More in detail, on the worker side, I include a third-order polynomial of age, a dummy variable for males, a dummy variable for having children, dummy variables for four education levels (pre-secondary, high school, post-secondary and post-graduate) interacted with dummies for age groups (20-29, 30-39, 40-49 and 50-60), and dummy variables for four civil statuses (single, married, separated, survivor). On the firm side, I control for sector-specific time trends with sector-year fixed effects[17], for

[17] I use the one-letter sector classification provided by Statistics Sweden. One-letter sectors are broader than two-digit sectors. For instance, the letter M sector belongs to services, includes seven two-digit sectors, and its description is *"Professional, scientific and technical activities"*.

location-specific factors with dummy variables for the region where the firm is based and for firm size with dummy variables for the firm's employment group category (5-19, 20-49, 50-99, 100 or more workers). Finally, I include a third-order polynomial of the tenure of each firm-worker employment relationship.

Following the original approach by Guiso et al. (2005), I focus on workers with steady employment and tenure histories. Therefore, the specification in (2) is estimated only on stayers, which I define as workers who remain employed at the same firm for more than two consecutive years. The measure of residual log earnings change I consider is then $\Delta\omega_{ijt} := \omega_{ijt} - \omega_{ijt-1}$.[18]

Figure 5 plots the standard deviation and Kelly's skewness of $\Delta\omega$ over time. As it is clear from the picture, the standard deviation exhibits no cyclicality while skewness turns negative during the Great Recession, which resonates nicely with the findings in Guvenen et al. (2014) and Busch et al. (2022).

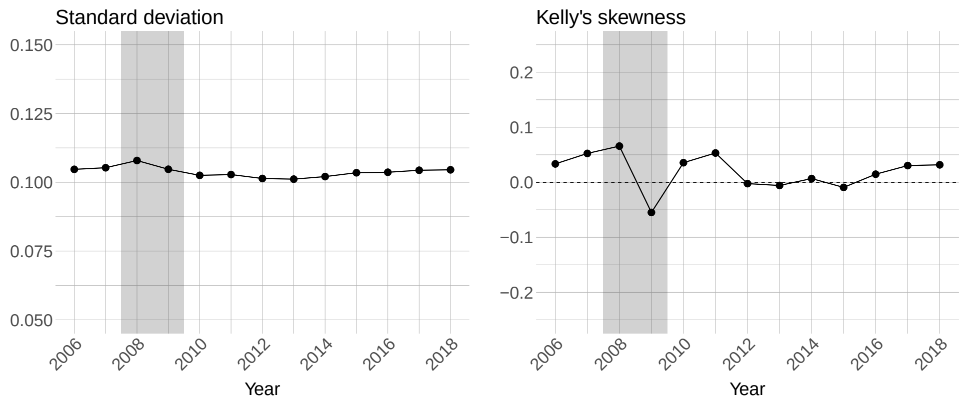

Figure 5: Measures of cross-sectional dispersion of residual log earnings changes over time.

2.5 Earnings changes and idiosyncratic firm shocks

In this section, I investigate the relation between the measures of idiosyncratic firm shocks (ν) and of residual log earnings changes ($\Delta\omega$).[19] To this end, I classify firms in fifteen bins - defined symmetrically around zero - according to the size of the shocks. Then, I compute the mean residual log earnings change $\Delta\omega$ for all the workers employed at firms in the bin. Figure 6 presents the results.

[18] It is worth noting that, while I am interested in the variation due to firm-related shocks, ω_{ijt} contains potentially both firm-related and worker-related shocks. However, because I am interested in the cross-sectional average of $\Delta\omega$ by firm TFP shock bins, the worker-related part should be at least partially controlled for.

[19] To limit the impact of outliers, idiosyncratic firm shocks are winsorized at 1 and 99 percent and residual log earnings changes at 5 and 95 percent.

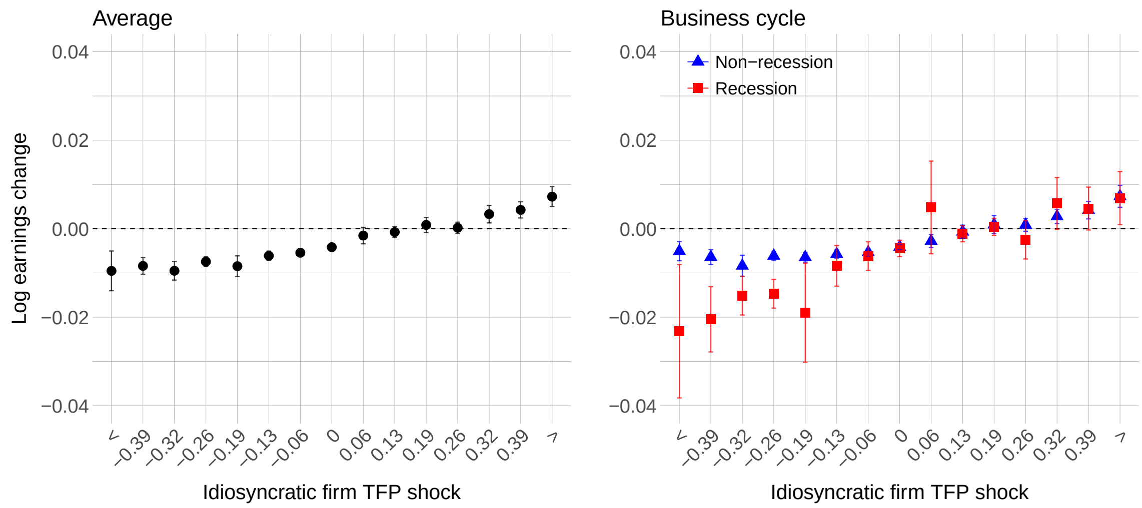

Figure 6: Average residual log earnings change over bins of idiosyncratic TFP firm shocks. *Left*: all years. *Right*: recessions (squares) and non-recessions (triangles). Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

Considering first the left part of the figure, which depicts pooled results, it is easy to see that, in general, firms pass through negative shocks. Nevertheless, the gradient is more pronounced for shocks closer to zero and gradually becomes flatter. The opposite pattern holds for positive ones, the pass-through of which is, thus, mainly driven by sizeable shocks. These findings are in line with the positive and significant pass-through coefficients found by the literature (e.g. Chan et al., 2020; Guiso and Pistaferri, 2020; Guiso et al., 2005).

The right panel, however, reveals that pooled results hide substantial business cycle heterogeneity. The pass-through of positive shocks is not state-dependent, as the pattern for recessions and non-recessions replicates the average case. On the other hand, firms provide, in general, significant insurance against negative shocks, but they pass them through much more in downturns.[20]

In order to give some magnitude to the trends shown in Figure 6, Table 3 shows the results obtained from running a regression of the residual log earnings change $\Delta\omega_{ijt}$ on firm shocks ν_{jt} when considering, respectively, all years, recessions and non-recessions.

[20]These findings contrast with the results obtained by Chan et al. (2020) using Danish administrative data on wages: in their paper, negative permanent shocks are always passed through regardless of the state of the cycle, while positive ones are passed through only in non-recessions.

Dependent variable: $\Delta\omega_{ijt}$, residual log earnings change						
	Average		Recession		Non-recession	
ν_{jt}	0.018***	0.023***	0.035***	0.020***	0.014***	0.024***
	(0.002)	(0.002)	(0.006)	(0.007)	(0.001)	(0.002)
$\nu_{jt} \cdot \mathbb{1}(\nu_{jt} < 0)$		−0.010**		0.026		−0.018***
		(0.004)		(0.020)		(0.003)
Obs. (Millions)	11.4	11.4	1.7	1.7	9.7	9.7
Monetary value (SEK)						
ν_{jt}	1,381	1,764	2,693	1,539	1,073	1,840
$\nu_{jt} \cdot \mathbb{1}(\nu_{jt} < 0)$		997		3,540		460

Table 3: The table reports the results from regressing residual log earnings changes on firm shocks. The first column reports the results when the sample includes all years, the second considers recessionary years and the third non-recessionary years. Clustered standard errors at the firm level in parenthesis. Confidence levels: 0.1 (*), 0.05 (**), 0.01 (***). Monetary values in 2020 SEK.

Before describing the results, it is worth noticing that the extreme cases of full and no insurance are represented, respectively, by zero and unitary regressions' coefficients. A number in between, thus, corresponds to different degrees of partial insurance.

The average elasticity of residual log earnings with respect to firms' shocks is 0.018, which is in line with 0.014, the pass-through coefficient of persistent shocks reported in the literature review by Guiso and Pistaferri (2020) for Sweden.[21] This implies a change in workers' average annual earnings of around 0.37 percent for a firm receiving a one standard deviation shock (about 0.20 log points on average). In monetary terms[22], this corresponds to 1,381 SEK. The limited magnitude of these numbers implies that firms, in general, are good insurance providers for their workers. Allowing the specification to accommodate an asymmetry between positive and negative shocks, reveals that the elasticity of the latter (which is the sum of the coefficient of ν_{jt} and the interaction term) is smaller, which reflects the previously highlighted gradient differences between shocks of different sign.

Concerning business cycle asymmetries, the results for non-recessions are - unsurprisingly, since almost all the years in the sample are classified as such - very similar to the average case.

[21] Which, in turn, is taken from a previous version of Balke and Lamadon (2022).

[22] To get the monetary equivalents, I multiply the relevant coefficient by one standard deviation shock and by average earnings in each subsample considered.

In recessions, instead, while the estimated elasticity of positive shocks is very similar, that of negative ones is much higher.[23] In monetary terms, the estimated coefficient of 0.020 (adopting the conservative approach of using the statistically significant part) corresponds to 1,539 SEK, which amounts to a non-negligible figure at the aggregate level, given that almost 15 percent of firms in the sample (which employ about 15 percent of workers) face a negative shock larger than one standard deviation in the recession.[24]

Robustness and heterogeneity. In Appendix C, I show that the empirical findings are robust to (i) the usage of different definitions of business cycle episodes and to (ii) the usage of an alternative measure of firm productivity that takes into account capital inputs used for production. I also investigate heterogeneity in the results in terms of firms' size, workers' age, and workers' tenure. Overall, the empirical patterns hold in all these dimensions, even though the business cycle asymmetry for negative shocks is slightly more significant for larger firms and more tenured workers.

Summing up. The empirical part of this paper has shown two facts. First, the transmission of negative idiosyncratic firm TFP shocks to workers' earnings is asymmetric over the business cycle: firms pass through these shocks much more in recessions. Positive shocks, on the other hand, are passed through especially if large, and this holds regardless of the state of the economy. Second, negative idiosyncratic shocks are more disastrous events for firms' profitability if they occur in recessions. The model outlined below will help to rationalize these empirical patterns.

3 Model

In this section, I develop a directed search model of the labor market that enables the investigation of idiosyncratic firm shocks' transmission to workers' wages. The model is very similar to the original framework developed by Menzio and Shi (2010), and its purpose of understanding the impact of firm shocks on labor market outcomes is close in spirit to the works of Balke and Lamadon (2022) and Schaal (2017).

[23]Note that, even if the coefficient for negative shocks in recessions is not significantly different from zero at the usual significance levels, the elasticity is anyways more than three times larger in recessions even when using the same estimated coefficient for both positive and negative shocks (0.020 vs. 0.006).

[24]When using 0.046 as elasticity, this amount is 3,540 SEK, which is even less negligible.

3.1 Environment

Agents and markets. The model economy is inhabited by a continuum of infinitely lived ex-ante identical workers and a positive measure of firms.

Firms maximize the present discounted value of profits at rate $\beta \in (0,1)$ by transforming with a constant returns to scale technology one unit of labor into $f(y,z)$ units of output. Aggregate productivity is denoted by $y \in Y = \{y_1, \ldots, y_{N_y}\}$ with N_y finite and $\underline{y} = y_1 < \cdots < y_{N_y} = \overline{y}$. Idiosyncratic firm productivity is denoted by $z \in Z = \{z_1, \ldots, z_{N_z}\}$ with N_z finite and $\underline{z} = z_1 < \cdots < z_{N_z} = \overline{z}$.

Workers derive utility from consumption according to the function $u(\cdot)$ - with $u : \mathbb{R} \to \mathbb{R}$ twice continuously differentiable, strictly increasing and weakly concave function - and maximize the present discounted value of utility at rate β. A worker can either be employed or not. In the former case, her consumption is equal to the wage paid by the firm where she works; in the latter, it is equal to the unemployment benefit b. There is no saving technology in this economy.

The aggregate state of nature s follows a Markov chain with a finite number of states governed by the transition probabilities $\Pi_s(\hat{s}|s)$.[25] and determines the value of aggregate productivity $y(s)$. Idiosyncratic productivity z also follows a Markov chain with a finite number of states governed by the transition probabilities $\Pi_z(\hat{z}|z,s)$, which are allowed to depend on the aggregate state.

The aggregate state of this economy ψ, therefore, includes the aggregate state of nature s but also the distribution of workers across unemployment and employment states, respectively $g_u \in [0,1]$ and $g_e : X \times Z \to [0,1]$ with $g_e(V,z)$ being the share of workers employed at a firm with idiosyncratic productivity z under a contract that guarantees to the worker an expected lifetime utility of V.

Workers look for jobs and firms post vacancies in a continuum of submarkets indexed by the expected utility the firm promises to give to the worker upon being hired in that submarket $x \in X = [\underline{x}, \overline{x}]$ with $\underline{x} < u(b)/(1-\beta)$ and $\overline{x} > u(f(\overline{y}, \overline{z}))/(1-\beta)$. Market tightness - the ratio of vacancies to workers searching for a job - in each submarket depends on the aggregate state and is denoted by $\theta(\psi, x)$.

There are four stages within each period: separation, search, matching, and production. In the separation stage, existing matches are exogenously destroyed with probability $\delta \in (0,1)$.[26] During the second stage, firms choose how many vacancies and in which submarket to post them at per-unit cost $k > 0$, and workers - both employed and unemployed - choose in which submarket to look for a job. Currently unemployed and employed workers search, respectively,

[25]The hat denotes variables in the next period.

[26]Differently to Menzio and Shi (2010), my model does not allow for endogenous separations.

with intensities $\lambda_u, \lambda_e \in (0, 1]$. Workers and firms in a given submarket are matched together into an employment relationship according to a constant returns to scale function during the third stage. More in detail, the job finding probability in a submarket with tightness θ is denoted by $p(\theta)$. As standard in the literature, $p : \mathbb{R}_+ \to [0, 1]$ is twice continuously differentiable, strictly increasing, strictly concave and it satisfies $p(0) = 0$ and $p'(0) < \infty$. Similarly, the job filling probability is $q(\theta)$ with $q : \mathbb{R}_+ \to [0, 1]$ twice continuously differentiable, strictly decreasing, convex function with $q(\theta) = p(\theta)/\theta$, $q(0) = 1$, $q'(0) < 0$ and $p(q^{-1}(\cdot))$ concave.[27] All new matches start with the same specific value of idiosyncratic productivity $z_0 \in Z$. In the production stage, each employed worker receives and consumes the wage w specified by the employment contract (described more in detail below) for producing $f(y, z)$ units of output. Unemployed workers consume the unemployment benefit $b \in (0, f(\overline{y}, \overline{z}))$. Finally, before the start of a new period, the new aggregate state of nature $\hat{s}$ and the new idiosyncratic productivity state $\hat{z}$ are drawn. Figure 7 depicts graphically the timing of actions in the model.

Contracting. Upon matching, the worker-firm relationship is disciplined by a contract that specifies the full series of wages $\{w_{t+j}\}_{j=0}^{\infty}$ for each possible history of the world (s^{t+j}, z^{t+j}). More specifically, in each period t, the firm chooses the wage path in each possible future history to maximize profits. Following the literature on recursive contracts (see Balke and Lamadon, 2022; Menzio and Shi, 2010, and references cited therein), it is possible to specify the firm problem recursively with the addition of future promised utility $\hat{V}$ as state variable. In other words, in each period, the firm chooses the current wage w and the future expected utility to give to the worker in each future state, that is $\hat{V}(\hat{\psi}, \hat{z})$. Because - as explained below - workers' optimal searching choice while on the job is a function of the future utility they would get in the current employment relationship, $\hat{V}(\hat{\psi}, \hat{z})$ will also be the relevant variable influencing their on the job choice upon realization of that future state. Commitment is only on the firm side: firms have to give the worker the expected utility specified by the contract - but can choose the split between wages today and future expected utility tomorrow. Workers, instead, are free to choose where to search while on the job. That is, firms will have to choose $\hat{V}(\hat{\psi}, \hat{z})$ so that workers' on-the-job search choices are consistent with the firm's profit maximization.[28]

[27] As explained in Menzio and Shi (2010), this assumption is needed to guarantee that the worker's problem is strictly concave and, hence, that it has a unique solution.

[28] This contractual environment is labeled "dynamic contracts" in Menzio and Shi (2010).

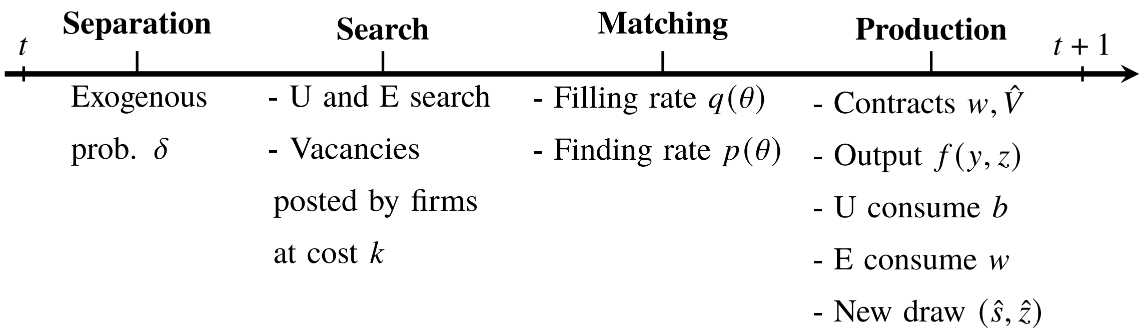

Figure 7: Timing of actions.

3.2 Worker's problem

Consider first the problem of an employed worker with current promised expected lifetime utility V who has to decide in which submarket x to direct her search while on the job. If she does not get to search, she will get V as specified by the contract. If she searches, instead, with probability $p\left(\theta(\psi, x)\right)$ she finds a new job that will give her expected lifetime utility x while with complementary probability she remains at her current job and gets the future utility specified by the contract. Mathematically, at the beginning of the search stage, the employed worker lifetime utility is $V + \max\{0, R(\psi, V)\}$ where R is the return to search function defined as:

$$R(\psi, V) = \max_{x \in X} p\left(\theta(\psi, x)\right)(x - V) \tag{3}$$

The solution of this problem returns the optimal searching choice $x^*(\psi, V)$ and the probability of leaving $\tilde{p}(\psi, V) := p\left(\theta(\psi, x^*(\psi, V))\right)$.

Let us now turn to the problem of an unemployed worker. At the beginning of the production stage, she consumes the unemployment benefit b and decides where to search in the next period, upon having the possibility to search. Her value is, therefore:

$$U(\psi) = u(b) + \beta\mathbb{E}\left[U(\hat{\psi}) + \lambda_u \max\{0, R(\hat{\psi}, U(\hat{\psi}))\}\right] \tag{4}$$

3.3 Firm's problem

Consider a firm who is matched with a worker whose lifetime utility specified by the contract is V when the aggregate state of nature is s and the idiosyncratic z. As previously described, conditional on survival of the employment relationship, the firm's problem is to maximize profits by choosing the wage to be paid today to the worker w and the future promised utility in each state of the world $\hat{V}$ subject to delivering the utility promised at the beginning of the period V.

Letting $\xi = (\psi, z)$, then the firm value is given by the following expression:

$$J(\xi, V) = \max_{w, \{\hat{V}(\hat{\xi})\}_{\forall \hat{\xi}}} f(y,z) - w + \beta(1-\delta)\mathbb{E}\left[\left(1 - \lambda_e \tilde{p}\left(\hat{\psi}, \hat{V}(\hat{\xi})\right)\right) J(\hat{\xi}, \hat{V}(\hat{\xi}))\right] \tag{5}$$

subject to:

$$V = u(w) + \beta \mathbb{E} \left[\delta U(\hat{\psi}) + (1-\delta) \left(\hat{V}(\hat{\xi}) + \lambda_e R(\hat{\psi}, \hat{V}(\hat{\xi})) \right) \right] \tag{6}$$

3.4 Market tightness

The firm chooses during the search stage how many vacancies to create and in which submarket to locate them. Its optimal choice on how many vacancies to create in submarket x when the aggregate state is ψ is determined by the benefit of creating a vacancy $q(\theta(\psi, x))J(\psi, z_0, x)$ and the cost of doing that k. The optimal strategy is therefore to create infinite vacancies in submarkets where the benefit is strictly higher than the cost and zero vacancies in submarkets where the cost is strictly higher than the benefit. Upon equality of the benefit and the cost, the firm is indifferent. Therefore, in any submarket that is visited by a positive amount of workers the tightness function is consistent with firm's optimal strategy if and only if:

$$k \geq q(\theta(\psi, x))J(\psi, z_0, x) \tag{7}$$

and $\theta(\psi, x) \geq 0$ with complementary slackness. In markets not visited by any worker, consistency requires $q(\theta(\psi, x))J(\psi, z_0, x)$ to be smaller or equal than k. However, following Menzio and Shi (2010), attention is restricted to equilibria in which the following slackness condition is satisfied in every submarket.

3.5 Equilibrium

The economy described above admits the following definition of equilibrium:

Definition 3.1. A recursive equilibrium is a market tightness function $\theta : \Psi \times X \to \mathbb{R}_+$, a return to search function $R : \Psi \times X \to \mathbb{R}$, a search policy function $x^* : \Psi \times X \to X$, a value function for unemployment $U : \Psi \to \mathbb{R}$, a firm value function $J : \Psi \times Z \times X \to \mathbb{R}$, a wage policy function $w : \Psi \times Z \times X \to \mathbb{R}$, a future promised expected utility function $\hat{V} : \Psi \times Z \times X \to X$ and a law of motion for the aggregate state $\Phi_\psi : \Psi \to \Psi$ such that:

- Market tightness θ is consistent with the firm optimal creation strategy (7) for all $(\psi, x) \in \Psi \times X$;
- Return to search R solves the problem in (3) and x^* is the associated policy function for all $(\psi, V) \in \Psi \times X$;
- Unemployment value satisfies (4) for all $\psi \in \Psi$;
- Firm value function solves the problem (5) and w and $\hat{V}$ are the associated policy functions for all $(\psi, z, V) \in \Psi \times Z \times X$;
- Aggregate law of motion of the economy Φ_ψ is derived from the policy functions $(x^*, w, \hat{V})$ and the exogenous processes governing s and z.

The above definition makes clear that the equilibrium objects of this economy are, in principle, functions also of the distribution of workers across the unemployment/employment states g_u, g_e, which would require solution procedures similar to the one developed by Krusell and Smith (1998) and make the computation of the equilibrium demanding. When the equilibrium depends on the aggregate state just through the aggregate state of nature s and not on the distribution of workers g_u, g_e, we say that such equilibrium is block recursive:

Definition 3.2. A block recursive equilibrium is a recursive equilibrium such that the equilibrium objects $\{\theta, R, x^*, U, J, w, \hat{V}\}$ depend on the aggregate state ψ just through the aggregate state of nature s and not through the distribution of workers g_u, g_e.

As in Menzio and Shi (2010), directed search implies the following proposition:

Proposition 3.1. *If the economy admits an equilibrium, then it is block recursive.*

Proof. See Appendix D. □

Therefore, the equilibrium depends on the aggregate state ψ just through the aggregate state of nature s and not through the distribution of workers g_u, g_e, which considerably simplifies the solution of the model.[29]

3.6 Trade-offs

To give some intuition on the main mechanisms in the model, in this section I discuss the trade-offs related to the optimization problems of the worker and the firm, respectively. Considering the worker first, the optimality condition of the maximization problem reads:

$$\frac{\partial p\left(\theta(s,x)\right)}{\partial x}(x - V) = -p\left(\theta(s,x)\right) \tag{8}$$

The above expression makes clear the trade-off experienced by the worker: on the one hand she would like to search in submarkets where he would receive higher lifetime utility, on the other, in equilibrium the probability of finding a job is decreasing in lifetime utility.

Turning to the firm, combining the first order conditions of its problem returns for each $\hat{\xi}$:

$$\frac{1}{u'(\hat{w})} - \frac{1}{u'(w)} = -\frac{\partial \log \tilde{p}(\hat{s}, \hat{V}(\hat{\xi}))}{\partial \hat{V}} \frac{\lambda_e \tilde{p}(\hat{s}, \hat{V}(\hat{\xi}))}{1 - \lambda_e \tilde{p}(\hat{s}, \hat{V}(\hat{\xi}))} J(\hat{\xi}, \hat{V}(\hat{\xi})) \tag{9}$$

Equation (9) clarifies the trade-off faced by the firm when deciding how much to change wages between two consecutive periods. On the one hand - the left side - changing the wage is costly because the firm would like to insure the worker against wage fluctuations. Indeed, because the worker is risk averse, by guaranteeing a stable wage the firm does not need to pay any risk premium. On the other hand - the right side - the firm benefits from changing the wage

[29] Appendix E describes the numerical solution procedure.

tomorrow (through its choice today of the state contingent promised utility tomorrow) because it keeps the worker's on-the-job search incentives aligned with the expected value of the match. Indeed, a firm experiencing a large positive idiosyncratic productivity shock would like to choose a high value for $\hat{V}$ in that state of the world to ensure that the worker is not poached and be able to enjoy the higher profits following from the shock.

Equation (9) is also important because it tells us the sign of wage changes. Specifically, since the first derivative on the right side is negative and the second term is positive, the change will either be positive or negative depending on the sign of J tomorrow.

In addition, it is worth noting that the crucial element to generating different relative marginal costs across states are searching frictions: without them, the model would prescribe full wage insurance against idiosyncratic shocks.

4 Calibration and estimation

The model is calibrated at the quarterly frequency. Below I describe (i) my choices for the functional forms of utility, production and matching functions (ii) the modeling and calibration strategy for the exogenous stochastic processes (iii) the parameters taken from the literature.

Functional forms. I adopt the following functional forms. For the utility function u I use the standard CRRA form. For the matching functions p and q I follow Menzio and Shi (2010). For the production function f I use an exponential function of aggregate and firm-specific productivities normalized by a constant a. Specifically:

$$u(x) = \frac{x^{1-\sigma} - 1}{1 - \sigma}, \quad p(\theta) = \theta\left(1 + \theta^{\gamma}\right)^{-\frac{1}{\gamma}}, \quad q(\theta) = p(\theta)/\theta = \left(1 + \theta^{\gamma}\right)^{-\frac{1}{\gamma}}, \quad f(y, z) = ae^{y+z}$$

Exogenous processes. Following Krueger et al. (2016), the aggregate state of nature s is modelled as a two-state (recession R and non-recession NR) first-order Markov process with transition matrix:

$$\pi_s(\hat{s}|s) = \begin{bmatrix} \pi_{\mathrm{R}} & 1 - \pi_{\mathrm{R}} \\ 1 - \pi_{\mathrm{NR}} & \pi_{\mathrm{NR}} \end{bmatrix}$$

The transition probabilities are calibrated as follows. Recall that the above process implies that the stationary probabilities of the two states $\pi_{\mathrm{R}}^{\infty}$ and $\pi_{\mathrm{NR}}^{\infty}$, and the expected length of a recession $\mathbb{E}(\mathrm{R})$ are determined by the following formulas:

$$\pi_{\mathrm{R}}^{\infty} = \frac{1 - \pi_{\mathrm{NR}}}{2 - \pi_{\mathrm{NR}} - \pi_{\mathrm{R}}}, \quad \pi_{\mathrm{NR}}^{\infty} = \frac{1 - \pi_{\mathrm{R}}}{2 - \pi_{\mathrm{NR}} - \pi_{\mathrm{R}}}$$

$$\mathbb{E}(\mathrm{R}) = 1 \cdot (1 - \pi_{\mathrm{R}}) + 2 \cdot \pi_{\mathrm{R}}(1 - \pi_{\mathrm{R}}) + \cdots = \frac{1}{1 - \pi_{\mathrm{R}}}$$

Thus, π_{R} can be calibrated to match the expected length of a recession and, given π_{R}, π_{NR} can be calibrated to match the fraction of time that the economy spends in the recessionary state. In my baseline empirical analysis I consider just the financial crisis - corresponding to the years 2008-2009 - as recession. Therefore, the frequency of recessions in Sweden over the time period 2004-2018, $\pi_{\mathrm{R}}^{\infty}$, is 13.3% and the average length of a recession, $\mathbb{E}(\mathrm{R})$, is 8 quarters. Using the formulas above, this delivers $\pi_{\mathrm{R}} = 0.875$ and $\pi_{\mathrm{NR}} = 0.981$.

The two values of log aggregate productivity y_{NR} and y_{R} with $y_{\mathrm{NR}} > y_{\mathrm{R}}$ are calibrated as follows. Normalizing the unconditional mean to one, the following relation holds:

$$e^{y_{\mathrm{R}}}\pi_{\mathrm{R}}^{\infty} + e^{y_{\mathrm{NR}}}\pi_{\mathrm{NR}}^{\infty} = 1$$

Thus, having a value for the ratio $e^{y_{\mathrm{R}}}/e^{y_{\mathrm{NR}}}$, it is possible to use the above equation to get the two values for aggregate productivity. In the data, the ratio at the end of 2009 is equal to 0.97, corresponding to a drop of 3 percent in real GDP per capita in recession rather than in normal times.[30] This implies that the two values for log aggregate productivity are $y_{\mathrm{NR}} = \log(1.004)$ and $y_{\mathrm{R}} = \log(0.974)$.

Two components discipline the behavior of the log of idiosyncratic firm productivity z. The first is labelled $\tilde{z}$ and follows an AR(1) process:

$$\tilde{z}_{jt} = \rho\tilde{z}_{jt-1} + \epsilon_{jt}, \quad \epsilon_{jt} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma^2\right)$$

The second is labelled ζ and follows a two-state Markov chain (with states $\{\bar{\zeta}, 0\}$ - I will refer to the first as "Low" and the second as "High" state - and $\bar{\zeta} \leq 0$) whose transition matrix depends on both the state of the economy and the sign of ϵ_{jt}. Therefore, the transition matrices for ζ are fully determined by eight parameters: the probability of remaining in state L conditional on being in it for non-positive and positive shocks and recessions and non-recessions, respectively $\pi^{-}_{\zeta,\mathrm{R,L}}, \pi^{+}_{\zeta,\mathrm{R,L}}, \pi^{-}_{\zeta,\mathrm{NR,L}}, \pi^{+}_{\zeta,\mathrm{NR,L}}$, and the probability of remaining in state H conditional on being in it for non-positive and positive shocks and recessions and non-recessions, respectively $\pi^{-}_{\zeta,\mathrm{R,H}}, \pi^{+}_{\zeta,\mathrm{R,H}}, \pi^{-}_{\zeta,\mathrm{NR,H}}, \pi^{+}_{\zeta,\mathrm{NR,H}}$.

Firm log productivity z is then equal to $\tilde{z}$ when the second component is in the high state and just equal to $\bar{\zeta}$ otherwise. Mathematically:

$$z_{jt} = \begin{cases} \zeta_{jt} & \text{if } \zeta_{jt} = \bar{\zeta} \\ \tilde{z}_{jt} & \text{if } \zeta_{jt} = 0 \end{cases}$$

This modeling choice is motivated by the fact that the two components serve for two different purposes: $\tilde{z}$ is supposed to capture the average behavior of firm productivity, while ζ should catch the empirical fact that, on average, negative shocks are more disastrous events in downturns.

[30] Compared to what a linear trend estimated on the full time range 2004-2018 would predict.

For this reason, I estimate the parameters governing them separately. Specifically, I estimate ρ and σ with SMM assuming ζ is inactive and matching the average standard deviation of firm productivity z and the average standard deviation (i.e. these are the averages computed using all years without conditioning on the state of the cycle) of the firm shocks ν in the data which are, respectively, 0.527 and 0.206.[31]

On the other hand, the process of ζ requires to calibrate nine parameters: $\bar{\zeta}$, $\pi^-_{\zeta,\mathrm{R,L}}$, $\pi^+_{\zeta,\mathrm{R,L}}$, $\pi^-_{\zeta,\mathrm{NR,L}}$, $\pi^+_{\zeta,\mathrm{NR,L}}$, $\pi^-_{\zeta,\mathrm{R,H}}$, $\pi^+_{\zeta,\mathrm{R,H}}$, $\pi^-_{\zeta,\mathrm{NR,H}}$, $\pi^+_{\zeta,\mathrm{NR,H}}$. I achieve this by matching moments related to the evidence on mass layoffs described in Section 2.3. More in detail, I proceed as follows. Because in the data there is not much difference in the duration of being in state L for positive and negative shocks, I set $\pi^-_{\zeta,\mathrm{R,L}} = \pi^+_{\zeta,\mathrm{R,L}} = \pi_{\zeta,\mathrm{R,L}}$ and $\pi^-_{\zeta,\mathrm{NR,L}} = \pi^+_{\zeta,\mathrm{NR,L}} = \pi_{\zeta,\mathrm{NR,L}}$. In addition, I set $\pi^-_{\zeta,\mathrm{NR,H}} = \pi^+_{\zeta,\mathrm{NR,H}} = 1$, which implies that firms can enter in the disaster state only upon receiving negative shocks in recessions, which is the relevant asymmetry in the data to be captured. This leaves five parameters to be estimated: $\bar{\zeta}, \pi^-_{\zeta,\mathrm{R,L}}, \pi^-_{\zeta,\mathrm{NR,L}}, \pi^-_{\zeta,\mathrm{R,H}}, \pi^+_{\zeta,\mathrm{R,H}}$. To get them, I adopt again SMM on the full process - using ρ and σ previously estimated - and match five moments: (i) the difference in the average share of firms experiencing mass layoffs upon receiving negative shocks between recessions and non-recessions (0.070), (ii) the same quantity for firms experiencing positive shocks (0.027), (iii) the average duration[32] of the L state for firms entering in it in recession (2.779 years), (iv) the ratio between the share of firms exiting the L state in three years in recessions and non-recessions (0.888) and (v) Kelly's skewness of ν in 2009 (-0.051).

The lower part of Table 4 reports the calibration outcome for the parameters governing the exogenous stochastic processes in the model and Appendix F describes in detail the estimation procedure.

Model parameters. The discount factor β is set as in Menzio and Shi (2010) equal to 0.987 in order to match an annual interest rate of about 5%. The unemployment benefit b is set as in Hagedorn and Manovskii (2008) equal to 0.955. As common in the literature, I normalize the search efficiency of the unemployed to one (e.g. Menzio and Shi, 2010). The separation rate δ is set to 0.022 in order to match the quarterly employment-to-unemployment rate in Sweden reported by Balke and Lamadon (2022). I set the vacancy cost to 0.049, the value used by Hagedorn and Manovskii (2008) divided by twelve as they have a weekly model. The matching

[31] Because the model is quarterly and the moments from the data are annual, I aggregate both $\tilde{z}$ and ζ at the annual frequency by taking their value in the last quarter. In addition, I define a year as recessionary if there are at least two consecutive quarters in which the economy is in downturn.

[32] In the data, I measure exit from L state as the first year - after the first year the firm experiences a mass-layoff - of positive employment growth.

function parameter is then set to 0.31 in order to match the unemployment-to-employment rate in Sweden as reported by Balke and Lamadon (2022). Finally, I set λ_e equal to 0.45 in order to match the job-to-job transition rate in Sweden from Balke and Lamadon (2022). The upper part of Table 4 summarizes the choices for these parameters.

Model parameters and functional forms

Parameter	Value	Description	Source/Target		
Externally calibrated					
σ	1.5	CRRA utility parameter	Balke and Lamadon (2022)		
β	0.987	Discount factor	Menzio and Shi (2010)		
k	0.049	Vacancy cost	Hagedorn and Manovskii (2008)		
b	0.955	Value of non-market activity	Hagedorn and Manovskii (2008)		
Internally calibrated					
δ	0.022	Separation rate	E2U rate. *Data:* 0.022. *Model:* 0.022.		
λ_e	0.45	Search efficiency, employed	J2J rate. *Data:* 0.026. *Model:* 0.029.		
γ	0.31	Matching function parameter	U2E rate. *Data:* 0.170. *Model:* 0.163.		
Normalizations					
e^{z_0}	1	Productivity new matches	Standard		
λ_u	1	Search efficiency, unemployed	Standard		
a	1/1.14	Firm productivity, constant	Average firm prod. in steady state equal to 1		
Stochastic processes					
Parameter	**Value**	**Description**	**Target**	**Data**	**Model**
π_{R}	0.875	Prob. stay in R state	Length recession (quarters)	8	
π_{NR}	0.981	Prob. stay in NR state	Recession frequency	0.133	
$e^{y_{\mathrm{R}}}$	0.974	Aggregate productivity in R	GDP per capita R/NR	0.970	
$e^{y_{\mathrm{NR}}}$	1.004	Aggregate productivity in NR			
ρ	0.979	Autocorrelation firm productivity	Average SD firm productivity	0.527	0.527
σ	0.106	St. dev. firm productivity shocks	Average SD firm shocks	0.206	0.206
$e^{\bar{\xi}}$	0.620	Disaster state	Kelly's skewness ν in 2009	−0.051	−0.041
$\pi^{-}_{\xi,\mathrm{R,H}}$	0.879	Prob. stay in H state, R, non-pos. shock	R-NR share firms mass layoffs upon neg. shocks	0.070	0.113
$\pi^{+}_{\xi,\mathrm{R,H}}$	0.986	Prob. stay in H state, R, pos. shock	R-NR share firms mass layoffs upon pos. shocks	0.027	0.018
$\pi_{\xi,\mathrm{R,L}}$	0.590	Prob. stay in L state, R	Duration (years) disaster state from R	2.779	1.710
$\pi_{\xi,\mathrm{NR,L}}$	0.885	Prob. stay in L state, NR	R/NR share firms exiting disaster state in 3 years	0.888	1.041

Table 4: Parameters.

5 Results

5.1 Inspecting the mechanism

To provide some intuition for the model mechanisms that generate the results described in the following sections, Figure 8 graphically represents the main elements of the theoretical framework.

Considering first the left part, the graph depicts the relationship between a risk-averse employed worker and a risk-neutral firm. As previously described, the firm is committed to delivering the worker a predetermined amount of promised utility V by choosing how much to give today through the wage w and how much through state-contingent promised utilities tomorrow $\hat{V}$. The optimal contract in this simple setting with no on-the-job search frictions and no business cycles prescribes constant wages. Indeed, by providing the worker full insurance against idiosyncratic shocks, the firm minimizes labor costs as it avoids paying the risk premium for wage fluctuations implied by the curvature of the worker's utility function.

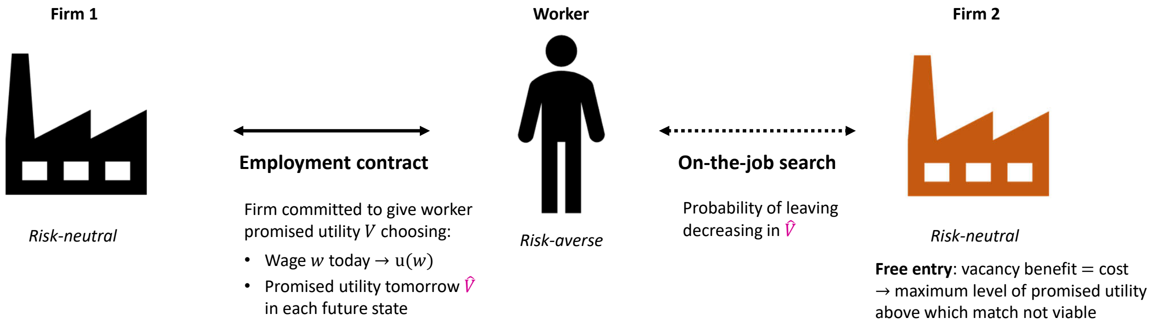

Figure 8: Graphical representation of the main elements of the model.

Turning to the model with on-the-job search, the firm now needs to consider that the choice of future promised utilities impacts the worker's probability of leaving. To make a concrete example, consider the case of a firm exposed to a negative idiosyncratic productivity shock. Because the shock substantially reduces the value of the match, the firm has a lower incentive to keep the worker. Thus, it will optimally choose a very low promised utility in that state of the world so that the worker will have a higher probability of being poached.[33]

Figure 9 reinforces the point by plotting the model-implied optimal policies of promised utility, probability of leaving and the implied wage equivalent[34] for a firm experiencing an idiosyncratic negative shock as functions of their current values (dashed line). When the shock realizes, the firm provides the worker a lower promised utility, which translates into a higher probability of leaving. In addition, because a lower wage profile can sustain the decreased value of promised utility, the firm also cuts wages.

[33]Therefore, the mechanism will be stronger the larger and more persistent the shock is.

[34]The wage equivalent of utility V is defined as the constant wage that the firm would need to give to the worker to achieve that utility, that is, is the wage w that solves $V = \frac{u(w)}{1-\beta}$.

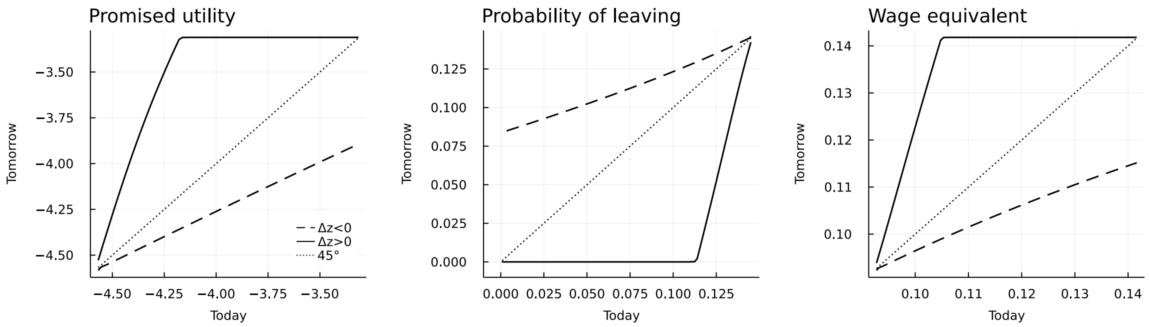

Figure 9: Policy functions of promised utility, probability of leaving and wage equivalent as function of their current values.

The graph also depicts the case of a firm exposed to a positive idiosyncratic productivity shock (solid line). While the mechanism works in the opposite direction, it is not symmetric because of the free entry condition. As illustrated in Figure 8 and in equation (7), the cost of posting a vacancy should equal the benefit of doing that. Hence, a maximum level of utility above which the match for an entering firm would not be profitable must exist. In turn, because only entering firms can poach workers, incumbents offering promised utility equal to the threshold effectively neutralize the effects of on-the-job search and, as prescribed by the frictionless model optimally provide full insurance - see equation (9). The implications of this discussion are evident in the discontinuities depicted in the picture. Losing the worker would be so damaging for a firm experiencing a positive shock that it offers the upper bound value even for relatively low values of the current promised utility.

Two facts support this mechanism as a good representation of what happens in reality. First, an immediate testable implication is that the probability of leaving should be a decreasing function of the size of the idiosyncratic firm shock. The right panel of Figure 11 shows that the data confirm this prediction. Second, compared to other OECD countries, Sweden features stricter than average employment protection (OECD, 2021). In such a setting, it is not hard to imagine that firms might be more prone to use other mechanisms - for example, incentive-based ones like those analyzed in this paper - rather than dismissal to achieve their employment objectives.[35]

Finally, two are the key factors allowing the model to replicate the business cycle asymmetry found in the data for negative shocks. The first is the general equilibrium effect from the lower job finding probability in recessions. Indeed, achieving the same probability that the worker leaves with a lower job finding rate requires a more significant decrease in promised utility.[36]

[35]The evidence presented in Appendix C.3 that the business cycle asymmetry for negative shocks is stronger for more tenured workers is consistent with this argument given that, in general, these employees are more difficult to fire.

[36]Similarly, achieving the same probability that the worker stays requires a less pronounced increase in promised

The second is modeling the increased probability of firm disaster in recessions, documented empirically in Section 2.3. Intuitively, this feature reduces even more the value of the match in recessions conditional on the firm being exposed to a negative idiosyncratic productivity shock, which strengthens the mechanism previously explained. The fact that the upper bound of utility binds in both recessions and non-recessions is instead crucial to deliver the non-state dependence of the pass-through of positive shocks.

5.2 Steady state

Figure 10 plots the average log wage change over the distribution of idiosyncratic firm productivity shocks resulting from simulating the model in steady state. Compared to its corresponding data version, the match is quite good.[37]

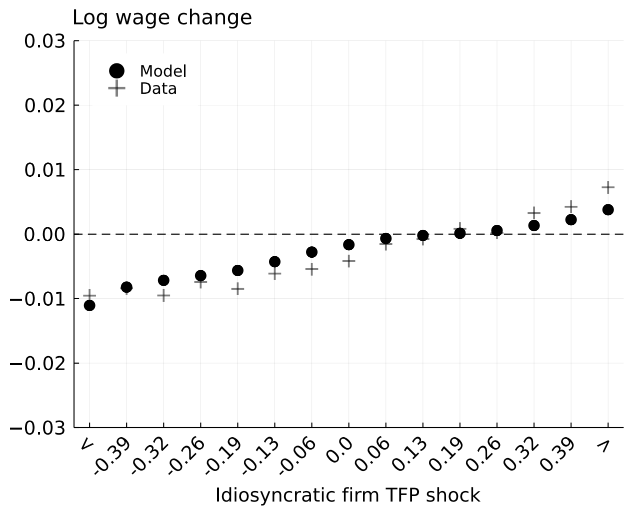

Figure 10: Average log wage change in steady state over the distribution of idiosyncratic firm productivity shocks.

As explained in the previous section, when a firm is exposed to a shock, it reoptimizes the worker's contract to align the promised utility with the new expected value of the match. Since the estimated persistence of the shocks is high, large negative shocks substantially reduce the expected value of the match. Thus, upon experiencing one, the firm has a lower incentive to

utility. However, as described below, unlike the scenario in which the firm wants the worker to leave, the general equilibrium effect, in this case, is not very significant in the current calibration.

[37]In the model, quarterly wages are aggregated at the annual frequency by summing their values over the four quarters, an individual is classified as a stayer upon remaining at the firm for all the four quarters, and a year is defined as recessionary if there are at least two consecutive quarters in which the economy is in downturn. To limit the impact of outliers, the wage growth distribution is winsorized at the top and bottom 1 percent (the same restriction applies for the results in all the sections from here onwards).

sustain the job relationship, and it optimally increases the chance that the worker is poached by promising a lower utility. In turn, a lower promised utility implies a lower wage. The closer a negative shock is to zero, the weaker the channel just described and, therefore, the smaller the pass-through.[38] Figure 11 validates this reasoning by showing that promised utility growth is decreasing and the probability of leaving increasing in the size - in absolute value - of the shock.

Regarding positive shocks, Figure 10 shows that the model matches well the corresponding patterns in the data. The reason for this is related to the upper bound level of promised utility. For values above that threshold, the poaching probability is zero, because it is not viable for a new firm to start a new match. Thus, since it is profitable for firms receiving positive shocks to keep the relationship alive, they immediately offer the worker values close to the threshold to minimize the probability of leaving. Remembering that the first order condition (9) implies that search frictions are the only reason for the lack of full insurance against idiosyncratic shocks, as the firm reduces the poaching probability, it also guarantees a smoother path of wages. Again, Figure 11 corroborates this reasoning by showing that promised utility growth increases and the probability of leaving decreases in the size of the shock.

The same picture also well depicts the non-linearity between the pass-through of positive and negative shocks implied by the threshold value of promised utility: the difference between the average probability of leaving for shocks in the central bin and in the first bin is about 0.05, while the same difference with the last bin is half of the size. A similar argument holds for promised utility growth. Although, as described above, this non-linearity is crucial to generate the flatter pass-through of smaller positive shocks, it also implies that the pass-through of the large ones in the model is slightly smaller than the actual values.

[38] Note that, unlike for positive shocks, there is no lower bound for the pass-through of negative ones. Thus, while providing a good match, the model misses capturing the flattening of the slope for large negative shocks in the average case (and, as depicted below, also in non-recessions).

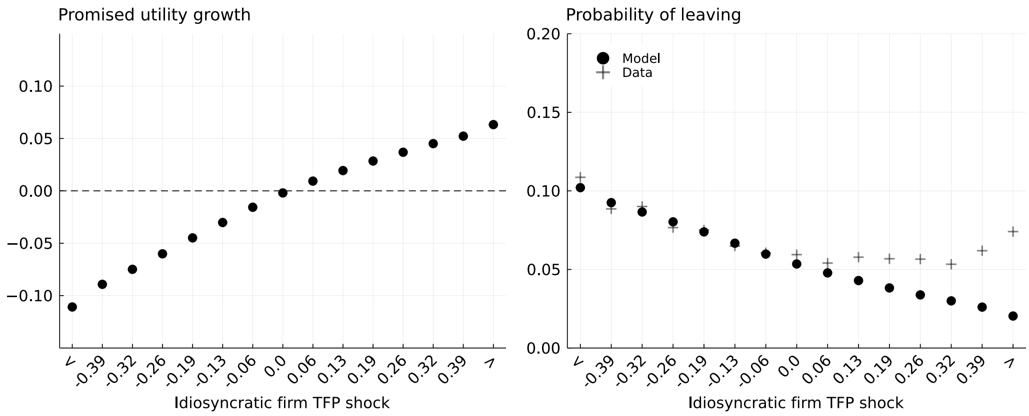

Figure 11: Promised utility growth and probability of leaving in steady state over the distribution of idiosyncratic firm productivity shocks.

By comparing the probability of leaving with the data, Figure 11 also provides supportive evidence in favor of the model's mechanism. Indeed, even though the empirical values for positive shocks are undershot, the probability of leaving is overall decreasing[39] across the support of firm's TFP shocks both in the model and the data. Remarkably, this outcome was obtained by targeting only the average job-to-job transition rate and not the full schedule.

The role of shocks' persistence. To further support the explanation provided above, Figure 12 compares the baseline pattern resulting from using the calibrated value of ρ against the ones obtained with different choices for the autocorrelation coefficient.[40] Indeed, the above discussion reveals a testable implication for the model mechanism: the lower the persistence of the shocks, the faster their reversion to the mean and, thus, to less extreme values of the match. In other words, the match's expected value after a large negative (positive) shock diminishes (increases) less for lower persistence values which should, in turn, make the model mechanism less strong.

[39]For large positive shocks it actually increases back, which suggests that other forces - not captured by the model - might be relevant in these cases.

[40]To ensure comparability across the different specifications, for each alternative value of ρ I change the normalization constant a in the production function to ensure that the average wage is the same as in the baseline economy.

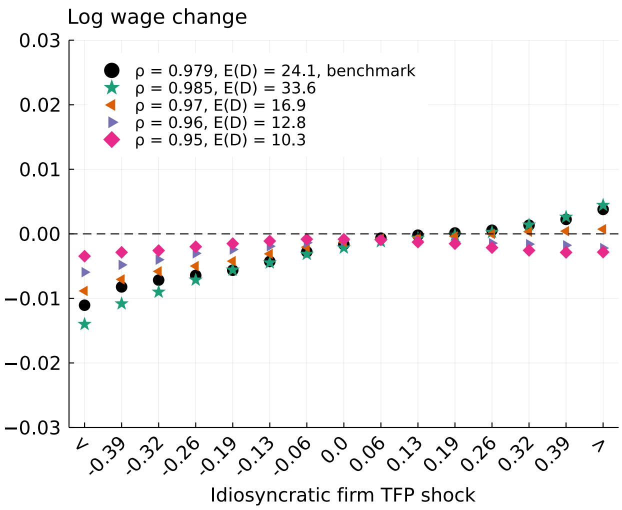

Figure 12: Average log wage change over the distribution of idiosyncratic firm productivity shocks for different values of the autocorrelation coefficient of firm productivity ρ. $\mathbb{E}(D)$ represents expected duration in quarters computed as $(1-\rho^2)^{-1}$.

Looking at the picture it is easy to see that this prediction is confirmed: the lower ρ is, the smaller the pass-through of shocks, especially if they are large, regardless of their sign. With lower persistence, large shocks have a smaller impact on the expected value of a match because they revert faster back to the mean. For negative shocks, this means that the firm is less willing to separate from the worker, which translates into smaller pass-through. On the other hand, for positive shocks, this means lower incentives to retain the worker, which also translates into smaller pass-through.

5.3 Business cycles

Building on the intuition behind the forces outlined in the previous section, I now use the full version of the model including the additional disaster state in recessions to describe the results for the pass-through of shocks over the business cycle.[41]

[41] In this version of the model, b, a and γ are state-dependent. I rescale b by aggregate productivity in recessions and non-recessions and set a so that in the two aggregate states average idiosyncratic firm productivity is one. This ensures that unemployment benefits constitute the same share of average firm productivity. Finally, the values of γ are set so that the job-finding rate from unemployment in non-recessions is slightly above the value in the pooled case (since almost all years are defined as non-recessionary), 0.165, and the ratio between the model-implied job-finding rate from unemployment in recessions and non-recessions is about 0.88, which is in line with the corresponding figure in the Current Population Survey. This results in γ equal to 0.328 in R and 0.315 in NR.

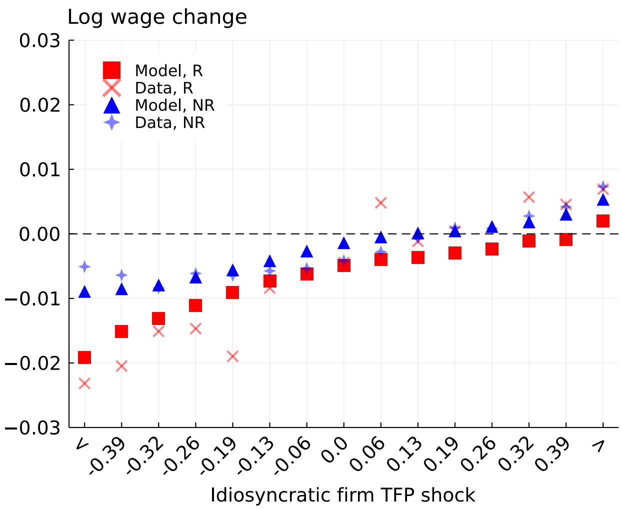

Figure 13: Average log wage change over the distribution of idiosyncratic firm productivity shocks, full model.

Figure 13 plots the average log wage change over the distribution of idiosyncratic firm shocks in recessions (squares) and non-recessions (triangles). Overall, the model is able to replicate the empirical patterns. The mechanisms behind the result are the same as the ones explained in the previous section. The upper bound of promised utility applies for positive shocks regardless of the business cycle, which explains the similar pattern for non-recessions and recessions. On the other hand, negative shocks are passed through much more in recessions because the possibility of disastrous events drastically reduces the expected value of the match which, in turn, boosts firms' incentives to dissolve the match.

It is worth remarking that, while general-equilibrium effects would push the model mechanism in the direction of generating more pass-through of negative shocks in recessions without the need for the additional disaster state, they are quantitatively not sufficient to match the empirical trends. To see this, Figure 14 compares the results obtained in the baseline specification with those obtained from a counterfactual economy without the disaster state.[42] While a negative idiosyncratic shock of a given size - especially if large in absolute value - is associated with a larger wage decrease in downturns, because the calibrated length of recessions is relatively short, the value of the match is still too high for the firm to substantially increase its willingness to separate from the worker.

[42] I also recalibrate the version of the model with business cycles but no disaster state following the same procedure described in footnote 41. In this case, γ is 0.302 in R and 0.309 in NR.

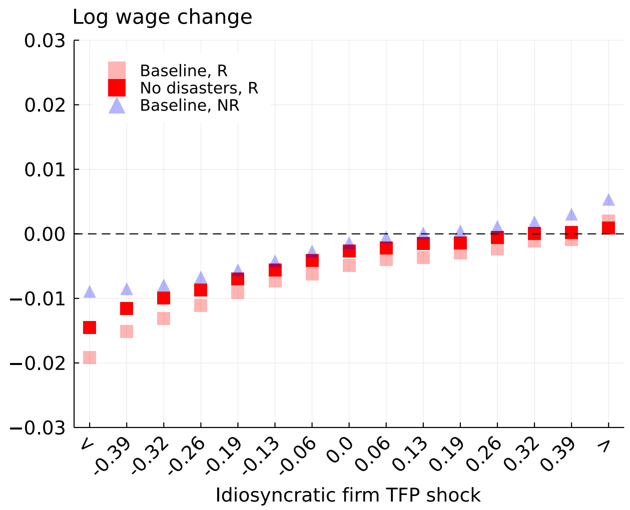

Figure 14: Average log wage change over the distribution of idiosyncratic firm productivity shocks, full model vs. model without firm disaster. state.

5.4 Implications for income risk over the business cycle

In a seminal paper, using administrative data from the US, Guvenen et al. (2014) show that the distribution of earnings changes features acyclical variance and procyclical skewness. These findings have later been extended to other countries with different institutional settings, namely Sweden, Germany, and France in a recent contribution by Busch et al. (2022). In Figure 5, I have shown that this also holds in my data when conditioning on my sample of stayers.

In principle, the mechanism outlined in the model can generate procyclical skewness. Indeed, if firms cut wages more in recessions upon receiving negative shocks and if the pass-through of positive shocks is much smaller and not state-dependent, this should generate more negative skewness when the economy is in a downturn.

To investigate the model's ability to generate the patterns in the data, Figure 15 plots Kelly's skewness and standard deviation of the cross-sectional distribution of log wage changes computed from model simulations. In line with the empirical findings, the distribution of log wage changes overall exhibits procyclical skewness and also acyclical standard deviation.[43]

[43]For readability, the figure reports only 40 years. Similar patterns hold over the whole simulation horizon.

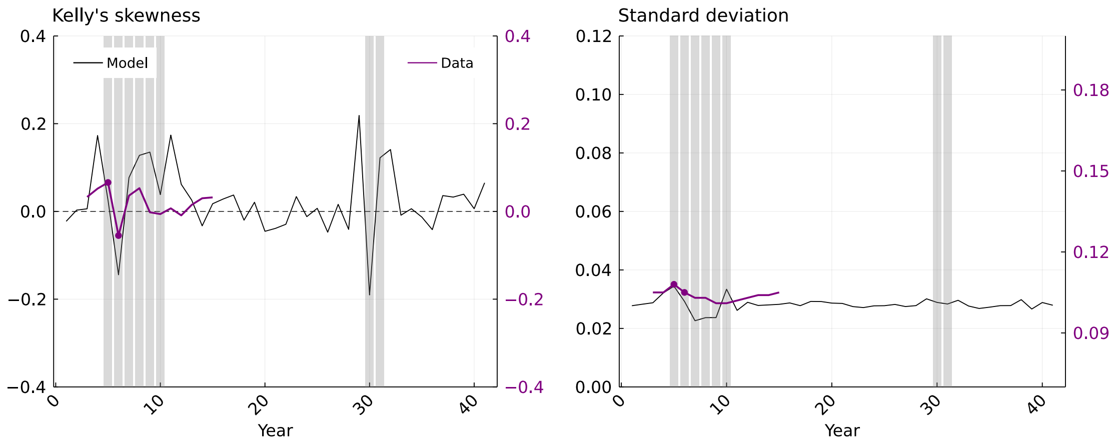

Figure 15: Kelly's skewness and standard deviation of the cross-sectional distribution of log wage changes over time computed from model simulations. Shaded areas correspond to recessions. The data series (right y-axis scale) is aligned so that the start of the recession in the data corresponds to the start of the recessionary period in the simulation. Recessionary periods in the data are indicated by dots.

This analysis supports the idea that it is rather the fact that more firms implement higher average wage cuts than the increased probability of extreme events that drives the behavior of the distribution in recessions. In addition, it also validates the model mechanism as an alternative explanation for business cycle trends in income risk and proves that wage pass-through is potentially one of their determinants.

5.5 Welfare cost of business cycles

Following the seminal approach in Lucas (1987), in this section I use the model to compute the welfare cost of business cycles. Let $\{c_{i,t}\}_{t=0}^{\infty}$ the consumption stream of individual i in the baseline economy without business cycles - with V its associated value function - and $\{\tilde{c}_{i,t}\}_{t=0}^{\infty}$ the stream in the alternative economy with business cycles - with $\tilde{V}$ its associated value function. The goal is to find how much consumption in the baseline economy the agent is willing to give up to avoid switching to the alternative economy. Mathematically, this means finding the value of λ that solves the following equation:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t u((1+\lambda)c_t)\right] = \mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t u(\tilde{c}_t)\right] \tag{10}$$

Having the two utility values V and $\tilde{V}$ for each individual, one can solve for λ in (10) to obtain the consumption equivalent between the two series under scrutiny.[44] However, it is not straightforward in economies with high degrees of heterogeneity which utility values to choose (Krusell et al., 2010). This also applies to my model, where each individual has a specific value of promised utility evolving dynamically (i.e. V is a state) and it is not obvious which are the correct values to consider for the solution of (10).

I proceed as follows. For each value of firm productivity z, I get the distribution of promised utilities in the baseline and alternative specifications. Then, I compare the average promised utility in each percentile between these distributions and weigh the resulting λ by the share of agents in that position in the baseline model. For the baseline, I use the stationary distribution of promised utilities implied by the model without business cycles. For the alternative, I consider the distribution obtained in each period from simulating the model with aggregate uncertainty. The λs recovered through the procedure just described represent, therefore, the change in consumption between two individuals in the same relative position in the distributions of utilities in steady state and period t. In other words, how much consumption an individual in a given position in the steady state distribution of utilities is willing to give up in order not to find herself in the same relative position in the period t distribution. This approach, therefore, enables to find a full cross-sectional distribution of λs in each period t, which can then be used for welfare comparisons. For instance, it is possible to compute the utilitarian consumption equivalent variation of the alternative economy by averaging the values of λ over all agents in the model in recessions, non-recessions, or all periods.

Table 5 reports the results. Overall, agents would be willing to give up 2.7 percent of their consumption to avoid aggregate uncertainty. While the numbers are relatively large compared to the literature, the lack of a saving technology and the presence of the disaster state make the effects of salary fluctuations particularly adverse in the model. Recessions are more costly than non-recessions, but the difference is not large as downturns are relatively short-lived in the used calibration.[45]

[44] Given the utility function $u(x) = \frac{x^{1-\sigma}-1}{1-\sigma}$ and the definition of the value functions as discounted streams of future utility, from equation (10) one gets:

$$(1+\lambda)^{1-\sigma}\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t \frac{c_t^{1-\sigma}}{1-\sigma}\right] = \mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t \frac{\tilde{c}_t^{1-\sigma}}{1-\sigma}\right] \iff (1+\lambda)^{1-\sigma}(V+\text{adj}) = \tilde{V}+\text{adj} \iff \lambda = \left(\frac{\tilde{V}+\text{adj}}{V+\text{adj}}\right)^{\frac{1}{1-\sigma}} - 1$$

with $\text{adj} = [(1-\sigma)(1-\beta)]^{-1}$.

[45] As seen in section 5.2, the pass-through of idiosyncratic firm shocks is relatively limited in steady state. Thus, the estimated costs of business cycles are not far from the welfare costs of not providing full insurance to the workers.

	All Periods	Recessions	Non-recessions
λ	-0.026	-0.027	-0.026

Table 5: Welfare costs of business cycles. Results refer to quarterly consumption.

6 Conclusion

Using Swedish administrative data covering the universe of firms, employment relationships, and workers, this paper has shown that earnings pass-through of idiosyncratic firm productivity shocks is asymmetric over the business cycle. Regardless of the state of the economy, a firm exposed to a positive shock passes it through mainly if it is sizable. On the other hand, firms are good insurance providers against negative shocks in normal times, but they pass them through much more in recessions. Specifically, compared to non-recessions, the earnings elasticity to negative shocks in downturns is more than three times higher. In monetary terms, a one standard deviation negative shock in recession implies - in the most conservative specification - a reduction in workers' annual salary by approximately 1,500 SEK (in 2020 terms). I have also documented that the share of firms experiencing mass layoffs upon receiving a negative idiosyncratic shock is about 7 percentage points higher in downturns. Combined with the fact that it takes around three years for them to return to positive employment growth, this shows that these shocks have larger and more persistent effects on the firm's profitability in recessions.

These empirical patterns have been rationalized in a directed search model of the labor market with on-the-job search, risk-averse workers, and firm commitment. The firm's trade-off between insuring the workers and making their on-the-job search choices aligned with the expected value of the match generates different degrees of pass-through across the distribution of idiosyncratic firm shocks. The non-state-dependent pass-through of positive shocks is delivered by the bound on the maximum utility that entering firms can offer to workers implied by the free-entry condition. Taking into account the more disastrous nature of negative shocks in recessions, instead, is crucial to generate their larger pass-through in downturns. As the model-generated wage growth distribution for stayers features procyclical skewness and acyclical variance, the theoretical framework also provides a new explanatory mechanism for recent empirical findings on business cycle trends in income risk. Welfare calculations reveal significant costs of business cycle fluctuations: to be compensated, workers would need to receive up to 2.7 percent of additional consumption.

The analysis presented in this work can be extended to several interesting avenues. First, while it is above the scope of this paper to provide a full analysis of the impact of the differences between my empirical strategy and the one adopted by Chan et al. (2020), my work shows that they seem relevant and deserve more investigation. In particular, it would be worth analyzing the effect of using earnings or wages as a measure of workers' salaries. Second, my analysis has considered the impact of pass-through on the average worker in a firm. It would be interesting to understand if the degree of insurance is heterogeneous also across different types of workers (e.g. white vs. blue collar). Third, this paper has focused on job market frictions to explain the empirical patterns found in the data. It would be relevant to understand if other mechanisms, such as firm labor market power (Chan et al., 2020), can also help rationalize them. Finally, the model provides a natural setting to study optimal public unemployment insurance over the business cycle in a context where firms already insure their workers. It is left to future research to investigate these important questions.

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A Additional figures

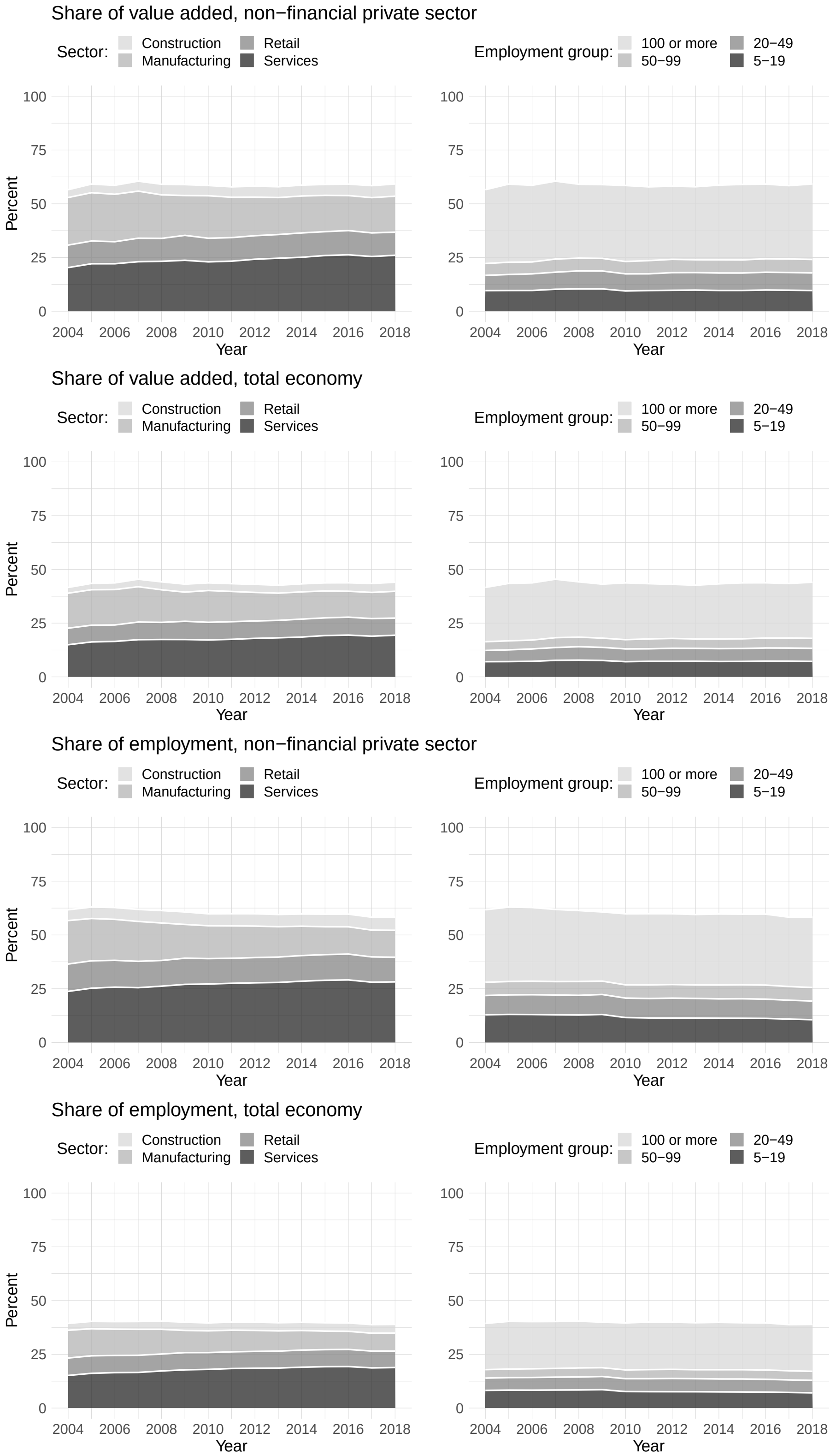

Figure A.1: Share of aggregate value-added and employment in the non-financial private sector (first and second rows) and in the whole economy (third and fourth rows) by sector and employment group.

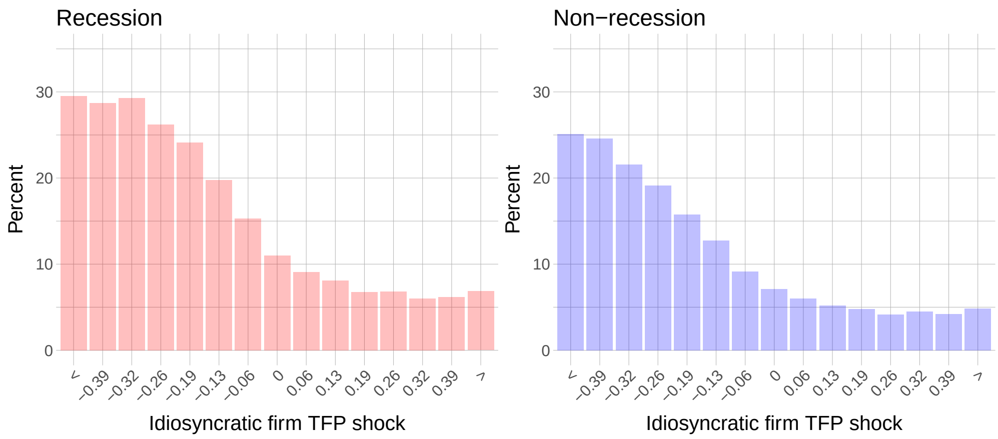

Figure A.2: Share of firms experiencing mass layoffs over the distribution of idiosyncratic firm TFP shock, recessions and non-recessions.

B Data and institutional background

Structural Business Statistics (SBS). Because the unit of analysis considered in this paper is the firm[46], I use the dataset *SBS företag* which contains balance sheet, accounting, industry codes as defined by Statistics Sweden (SNI) and some other company information at the firm level. The time range of the sample I analyze is 1997-2018: before 1997 not all Swedish firms are included in the data and the last year available is 2018. I drop observations with missing firm identifier and firms having more than one entry per year. I also exclude observations without SNI code or for which I cannot convert the SNI code according to the 2007 definition.[47] Furthermore, I exclude firms that are classified as financial companies, firms with negative wage bill, firms with zero wage bill but at least one employee and firms with negative operating expenses. Monetary variables are deflated using the CPI for Sweden.

Register-Based Labour Market Statistics (RAMS). On the firms' side, RAMS includes information on employment, juridic status, sector of activity and municipality from 1985 to 2019. The observation level is the establishment. I exclude observations with missing firm or establishment identifier and with missing information on the juridic form and municipality.

[46]A firm in the dataset is a legal entity that can include one or more establishments. More firms can be owned by the same mother company.

[47]In the time range I consider SNI definitions changed twice. Specifically, the relevant SNI definition is SNI 1992 until 2002, SNI 2002 between 2003 and 2008 and SNI 2007 afterwards. In order to get a consistent definition of SNI codes across years, I extend the SNI 2007 definition back in time. To do this I use conversion files provided by Statistics Sweden and, when the conversion is not one-to-one, I use the most common transition in the data which I obtain by counting the number of transitions in the years around the switch in SNI definition.

Because municipality is observed at the establishment level and the unit relevant for my analysis is the firm, every time there is more than one municipality associated to a firm in a given year, I assign to the firm/year observation the municipality where most establishments are located and, if there is a tie, that of the establishment with higher number of employees. From the municipality codes I also recover the region in which the firm is based.

On the workers' side, RAMS includes, for every employed individual, the establishment and firm identifiers of all the workplaces she is employed at, the starting and ending month of each employment relationship, a measure of the salary received in each employment relationship and the occupational status of the worker (employee, self-employed, etc.) for the time period 1985-2019. I exclude observations with missing firm of worker identifier, those with missing information on the initial and final month of the employment relationship and I focus only on workers whose occupational status is of employee and who are employed at least six months in a year. Furthermore, if a worker has more than one employment relationship in a given year, for that year I classify that worker as employed at the firm where she receives the highest salary. Based on this, I construct a tenure indicator that keeps track of the number of years an employment relationship has been going on, a variable that counts the number of employees in each firm, and an annual measure of earnings by annualizing the salary received at the firm[48] where she has been classified to work at in that year as explained before. Monetary variables are deflated using the CPI for Sweden.

Longitudinal Database on Education, Income and Employment (LOUISE). This dataset contains socio-economic and demographic information for each Swedish resident for the period 1985-2019. I set the lower bound of the time range to 1998 as before this year data on some civil statuses are not available. From this dataset I recover a household identifier, the civil status, gender, year of birth, number of children and education. I exclude observations with missing information on individual and household identifier, gender, year of birth, number of children, education or civil status and people with more than six children. I also merge education levels to get four levels (pre-secondary, secondary, post-secondary and post-graduate) and civil statuses to get four categories (singles, married, separated, survivors). Furthermore, I construct dummy variables capturing the period when a person becomes married, remarries or separates (by either divorcing or becoming a survivor). In addition, using the household identifier, I link married people to their partner and drop observations which are registered as married but for whom I did not get a match to find their partner.

[48]This is done by dividing the total salary paid by the number of months in which the employment relationship has been active and multiplying the result by twelve.

Aggregate data. Nominal GDP, CPI (reference year 2020) and the unemployment rate are taken from the OECD Economic Outlook 110 (December 2021). Total and sectoral value-added and employment are taken from SCB's website: the data are quarterly so I aggregate them at the annual frequency by summing up the quarterly flow values in each year for value-added and and by averaging across the four quarters for employment. The OECD recession indicator ("OECD based Recession Indicators for Sweden from the Period following the Peak through the Trough, +1 or 0, Monthly, Not Seasonally Adjusted") was downloaded from FRED. Aggregation from monthly to annual is done as follows. First, I define a quarter as recessionary if the monthly indicator is one in all the three months of the quarter. Then, I define a year as recessionary if there are at least two consecutive recessionary quarters.

Institutional background. As pointed out by Guiso et al. (2005), in labor markets characterized by high levels of centralized wage bargaining there is much less leeway for firms to pass idiosyncratic shocks to workers' salaries. In this section, therefore, I briefly discuss some features of the Swedish institutional background in order to provide evidence that a substantial part of workers has at least part of their salaries determined at the firm level. The main source for this section is Topel and Fredriksson (2010).

While union membership rates in Sweden have been very high (around 80%) since the 70s, wage-setting institutions have changed quite considerably in the last fifty years. The highly centralized procedures in place during the 70s have indeed been gradually displaced in favor of decentralized agreements. Table B.1 presents the wage agreement models present in the Swedish labor market in 2004 together with the percentage of employees in the private sector covered by each type of model.[49]

[49]A fallback means that the central agreement specifies a general wage increase that comes into operation should the local parties not agree. A guaranteed wage increase means that each individual is guaranteed a wage increase of a certain amount of Swedish krona (SEK). A local wage frame means that the local parties are given a total wage increase but can decide on the distribution of that increase over individuals.

Model	Employees (%)
1. Local bargain without restrictions	7
2. Local bargain with a fallback	8
3. Local bargain with a fallback plus a guaranteed wage increase	16
4. Local wage frame without a guaranteed wage increase	12
5. Local wage frame with guarantee or a fallback regulating the guarantee	28
6. General pay increase plus local wage frame	18
7. General pay increase	11

Table B.1: Percentage of employees in the private sector under different wage agreement models. *Source:* Topel and Fredriksson (2010) based on National Mediation Office (2004).

The table reveals that, while there is substantial heterogeneity in the distribution of wage agreement models - with at the exterma 11% of workers subject only to the central agreement and 7% to local bargain without restrictions - 89% of workers are into agreements in which potentially at least part of the salary is determined at the local level and 19% in local agreements in which a wage increase is not guaranteed. Therefore, there is room for firm performance to be reflected in workers' wages.

C Robustness

C.1 Alternative definitions of business cycles

In order to check that the main empirical finding is not determined by the business cycle episodes classification, I have also experimented with two alternative definitions: (i) defining recession 2008-2009 and non-recession 2014-2015 (ii) defining recessions using the OECD recession indicator for Sweden.[50] Figure C.3 plots GDP growth and the unemployment rate when using these alternative definitions.

[50]See Appendix B for more details on the OECD indicator.

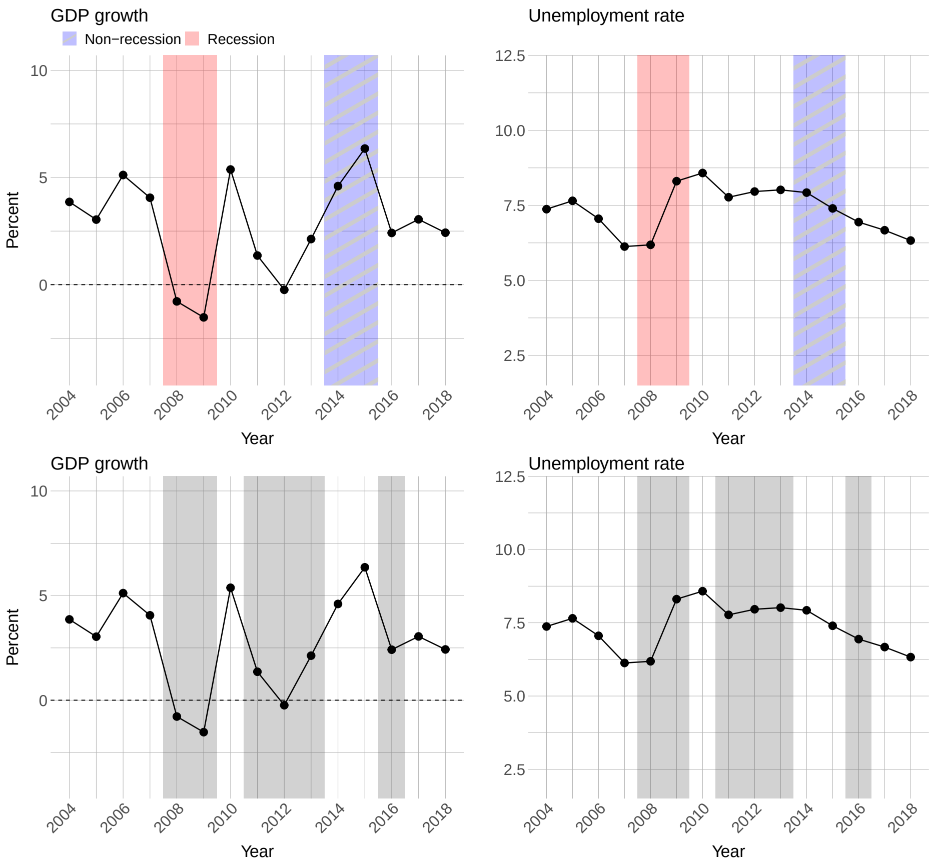

Figure C.3: GDP growth and unemployment rate in Sweden and alternative business cycle definitions. *Top:* recession 2008-2009, non-recession 2014-2015. *Bottom:* recessions and non-recessions defined according to OECD recession indicator.

Figure C.4 reports the earnings pass-through graphs for these alternative definitions. Even though when using the OECD indicator the distinction for negative shocks between recessions and non-recessions becomes slightly less stark, overall the two pictures clearly indicate robustness of the main empirical result.

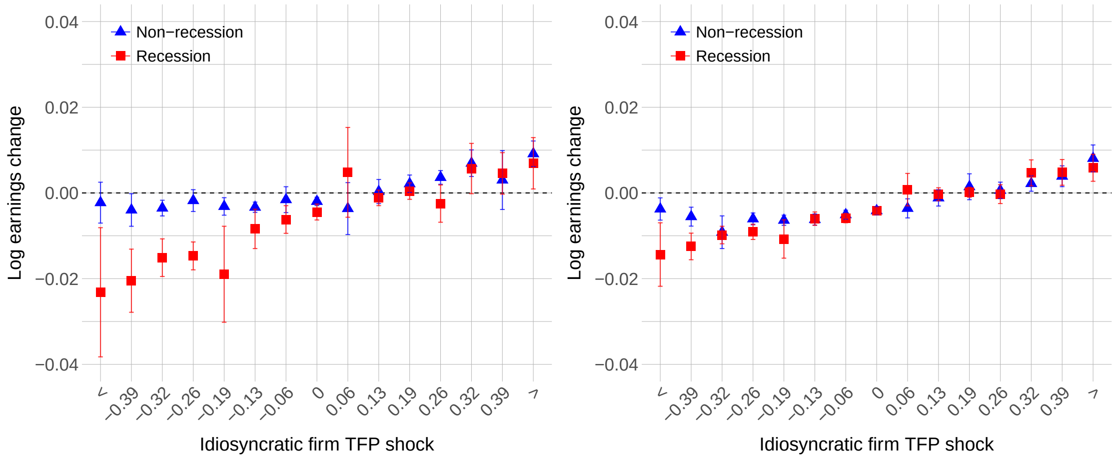

Figure C.4: Average residual log earnings change over bins of idiosyncratic firm shocks for alternative business cycle definitions. *Left*: all years. *Right*: recessions (squares) and non-recessions (triangles). Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

C.2 Alternative measure of firm productivity

In order to check the robustness of the results to the measure of firm productivity used in the baseline analysis - log value-added per worker - in this section I replicate the main empirical finding using an alternative definition. Following - among others (see Syverson, 2011, for a review) - Bloom et al. (2018) and Salgado et al. (2020), under the assumption that the firm production function is Cobb-Douglas, it is possible to recover a measure of firm productivity as the residual of the following equation:

$$\log Y_{jst} = a^N_{st} \log N_{jst} + a^K_{st} \log K_{jst} + z_{jst}$$

where Y_{jst} is value-added of firm j operating in sector s at time t, N_{jst} and K_{jst} are, respectively, measures of the labor and capital inputs used in the production process, a^N_{st} and a^K_{st} the factor shares and the residual, z_{jst}, is firm productivity.

Practically, to recover z with this approach, I proceed as follows. First, I compute the labor share a^N_{st} as the ratio between the total wage bill and total value-added in each two-digit sector s and each year t.[51][52] Using the identity $a^K_{st} = 1 - a^N_{st}$ I obtain the capital share. Then, using the wage bill as measure of N, total fixed assets as measure of K and the measure of value-added already available in the data as Y, I recover z_{jst} from the above formula. Finally, I run regression (1) using this new measure of productivity and recover the new shocks ν_{jt}. Figure C.5 presents

[51] All the monetary variables used are in 2020 SEK.

[52] I exclude the sector-year cells with less than 100 firms.

the results. Overall, even though the magnitude of wage changes is smaller and positive large shocks do not seem to be passed through much, the trends reported in the baseline are robust.

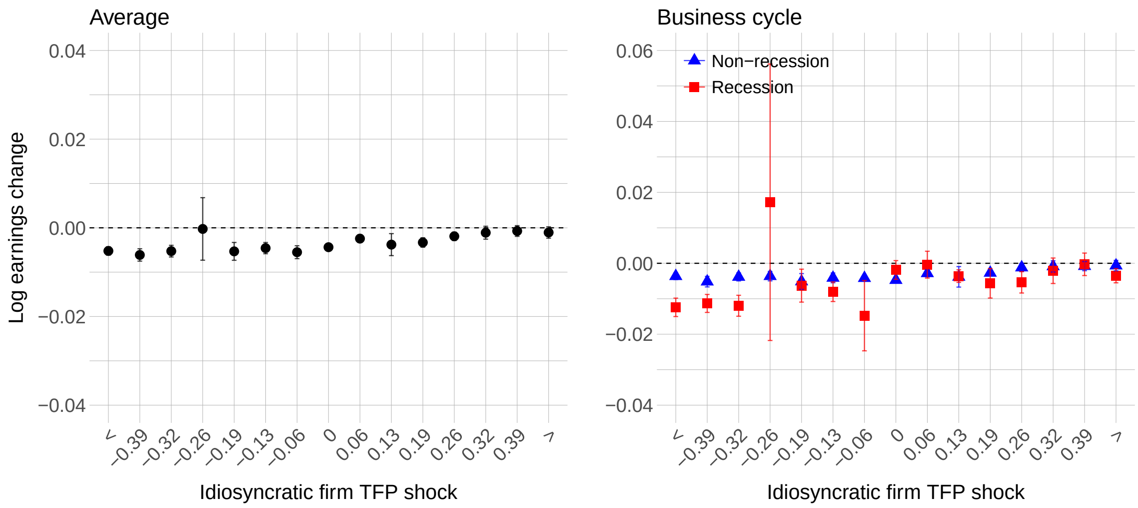

Figure C.5: Average residual log earnings change over bins of idiosyncratic firm shocks for alternative firm productivity definition. *Left*: all years. *Right*: recessions (squares) and non-recessions (triangles). Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

C.3 Heterogeneity

In this section, I investigate possible heterogeneities in the results documented in the empirical section of the paper.

Figure C.6 plots the residual log earnings changes for firms of different sizes (number of employees between 5-19, 20-49, 50-99 and 100+). Overall, the patterns are still there for all the four groups, even though the business cycle asymmetry for negative shocks is slightly larger for larger firms.

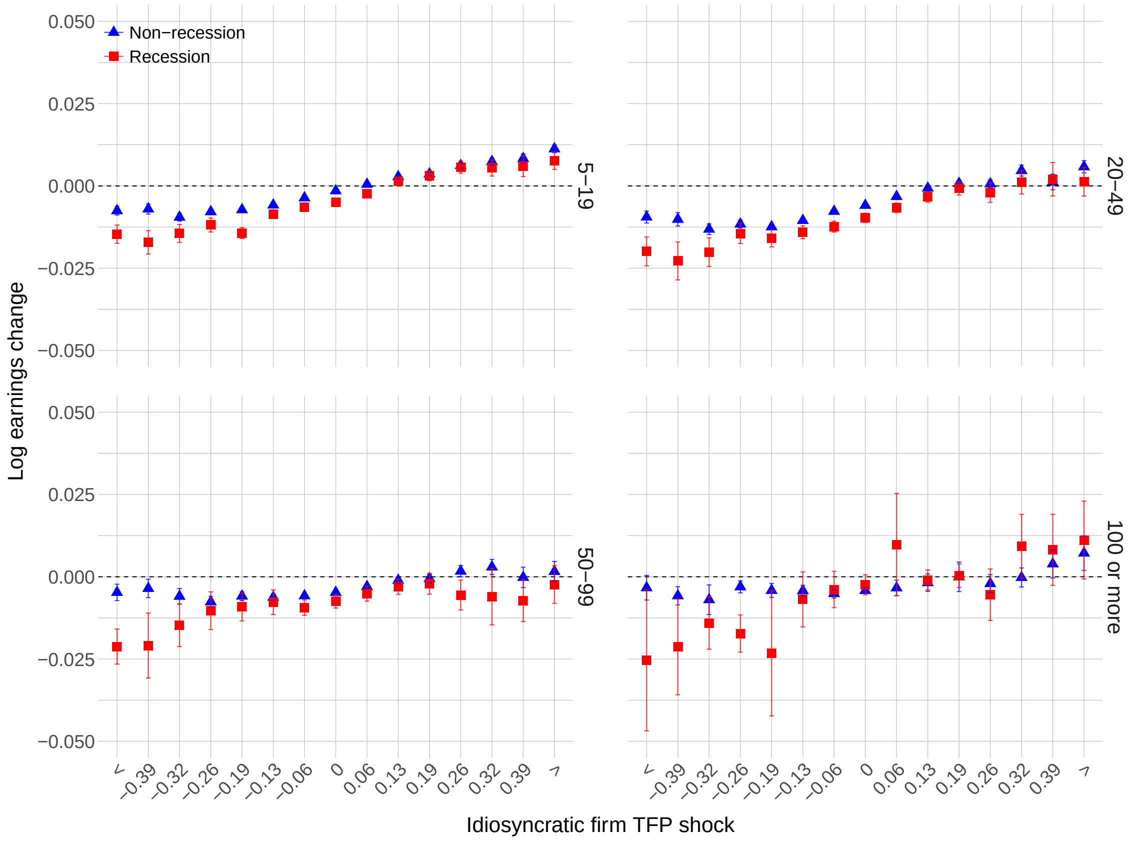

Figure C.6: Average residual log earnings change over bins of idiosyncratic firm shocks, firms' size heterogeneity. Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

Figure C.7 plots the same thing for workers in different age bands (20-33, 34-47, and 46-60). In general, the empirical trends still hold across all groups.

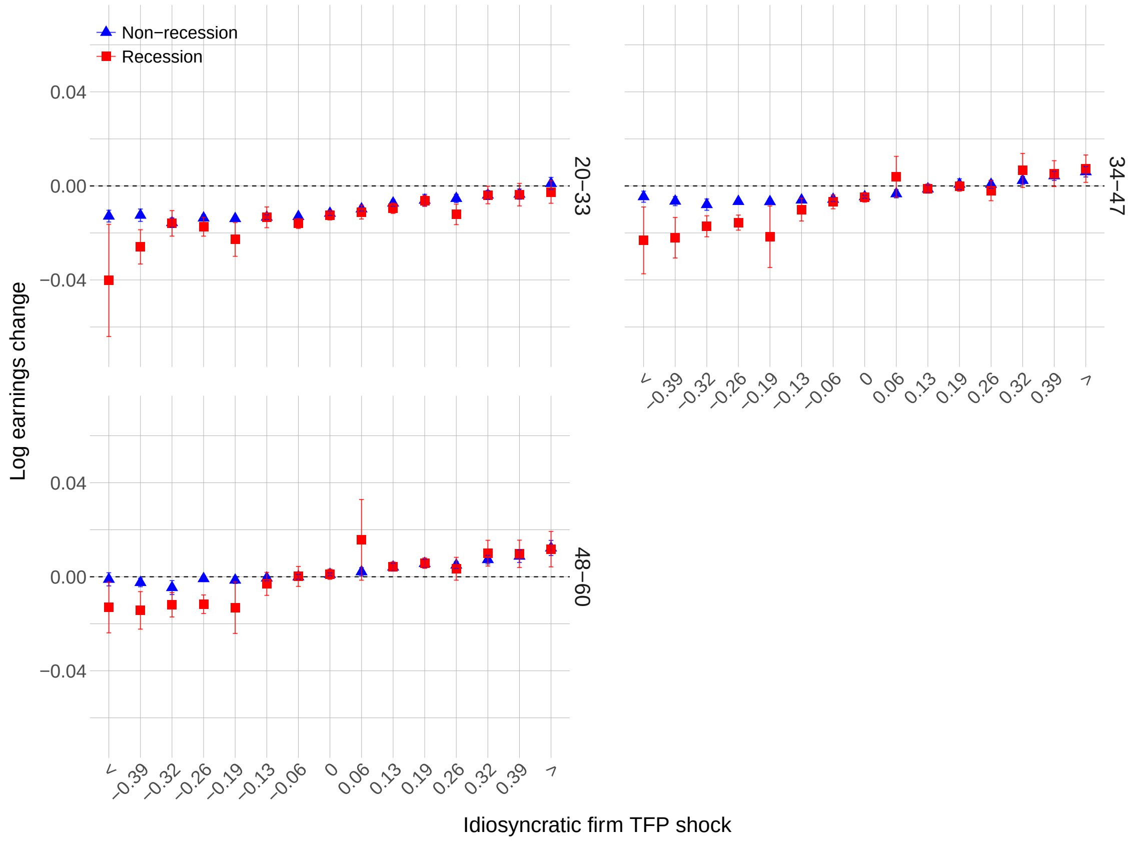

Figure C.7: Average residual log earnings change over bins of idiosyncratic firm shocks, workers' age heterogeneity. Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

Figure C.8 investigates heterogeneities in workers' tenure (I divide workers in three groups, with *low* indicating shorter tenure and *high* longer tenure). Again, the empirical patterns are overall still there, even though the negative shocks' asymmetry is stronger for more tenured workers.

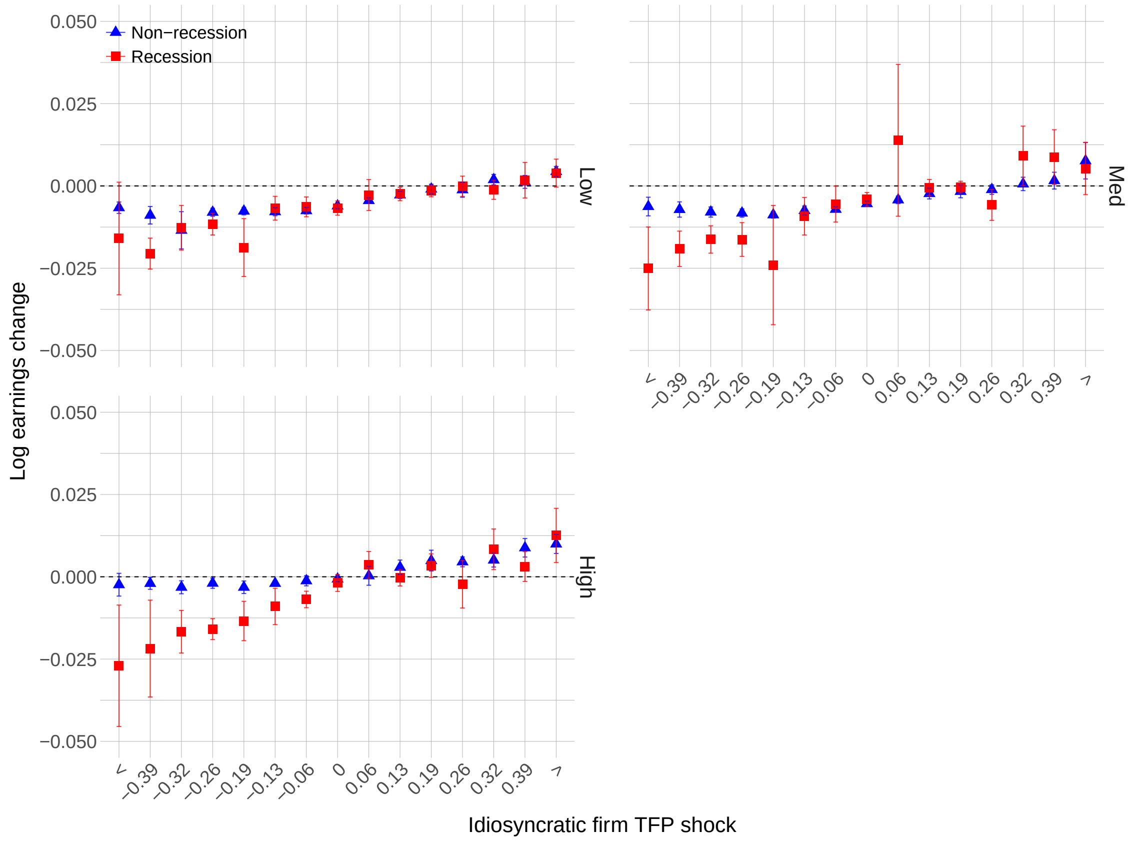

Figure C.8: Average residual log earnings change over bins of idiosyncratic firm shocks, workers' tenure heterogeneity. Confidence intervals are at the 90 percent level and standard errors are clustered at the firm level. The first bin contains all firms below the −0.39 bin and the last all firms above the 0.39 bin.

D Block recursivity of the equilibrium

As per definition 3.2, proving that the equilibrium of the model economy is block recursive requires to show that the equilibrium objects $\{\theta, R, x^*, U, J, w, \hat{V}\}$ depend on the aggregate state ψ just through the aggregate state of nature s and not through the distribution of workers g_u, g_e. Following closely Menzio and Shi (2010), the proof will consist in showing that each of the equilibrium objects and the operator T for updating the firm value satisfy this property.

Let $\mathcal{J}(Y \times Z \times X)$ be the set of firm value functions $J : Y \times Z \times X \to \mathbb{R}$ satisfying properties (J1)-(J3) described in Menzio and Shi (2010). Take an arbitrary function $J \in \mathcal{J}$. For all $(\psi, x) \in \Psi \times X$ satisfying $J(y, z_0, x) \geq k$ the market tightness implied by the equilibrium condition (7) is $q^{-1}\left(\frac{k}{J(y,z_0,x)}\right)$ and for all $(\psi, x) \in \Psi \times X$ such that $J(y, z_0, x) < k$ tightness is zero. Given the properties of J, the former condition is satisfied if and only if $x \leq \tilde{x}(y)$, where

$\tilde{x}(y)$ solves $J(y, z_0, x) = k$. Therefore, market tightness can be summarized as follows:

$$\theta(y, x) = \begin{cases} q^{-1}\left(\frac{k}{J(y,z_0,x)}\right) & \text{if} \quad x \leq \tilde{x}(y) \\ 0 & \text{otherwise} \end{cases}$$

As it is clear from the above expression, the market tightness function θ depends on the aggregate state ψ only through aggregate productivity y. Intuitively, since the firm value does not depend on the distributions g_u, g_e and the cost of creating a vacancy is constant, the probability of filling a vacancy - and thus tightness - is independent of the distribution of workers. In addition, the properties of J and q imply that tightness is decreasing in x. Intuitively, it is easier to attract a worker - and thus to fill a vacancy - by promising her higher utility.

Turning to the return to search function R, note that, given θ, for all $(\psi, x) \in \Psi \times X$ the objective function $\max_{x \in X} p\,(\theta(y, x))\,(x - V)$ in (3) depends on the aggregate state just through aggregate productivity. In addition, the choice set X does not depend on the aggregate state of the economy. Thus, the optimal search decision m and the return to search functions R depend on the aggregate state just through y and not through g_u, g_e. Intuitively, this follows from the fact that both the two terms in the objective function - the job finding probability and the return - are independent of the employment status of other workers.

In turn, letting $\mathcal{U}(Y)$ be the set of unemployment values $U : Y \to \mathbb{R}$ starting from any initial guess $U \in \mathcal{U}$ the operator in equation (4) is a contraction mapping in which the updated value of unemployment in each iteration depends on the aggregate state just through y and not on the distribution of workers because both the unemployment benefit and the return to search are independent of the distribution of workers.

With all the above it is now possible to construct the updated value of the firm $\tilde{J}$ by plugging the elements just described in the optimization problem of the firm:

$$\tilde{J}(y, z, V) = \max_{w, \{\hat{V}(\hat{y},\hat{z})\}_{\forall(\hat{y},\hat{z})}} f(y, z) - w + \beta(1-\delta)\mathbb{E}\left[\left(1 - \lambda_e \tilde{p}\left(\hat{y}, \hat{V}(\hat{y}, \hat{z})\right)\right) J(\hat{y}, \hat{z}, \hat{V}(\hat{y}, \hat{z}))\right]$$

subject to:

$$V = u(w) + \beta\mathbb{E}\left[\delta U(\hat{y}) + (1-\delta)\left(\hat{V}(\hat{y}, \hat{z}) + \lambda_e R(\hat{y}, \hat{V}(\hat{y}, \hat{z}))\right)\right]$$

Because the objective function above and the choice sets depend on aggregate productivity y but not on the distribution of workers, the same holds true for the updated value of the firm. Intuitively, this is a consequence of the fact that the match output, the match survival probability and the continuation value are depend on y but not on g_u, g_e. Repeating the same argument by using as new firm value $\tilde{J}$ it is possible to conclude that the operator defining the equilibrium value of the firm T also depends on y but not on g_u, g_e, which completes the proof.

E Numerical solution

E.1 Discretization and grids construction

I have already specified in Section 4 of the main text the processes for aggregate productivity y and for firm TFP z, so in this section I will describe just the construction of the grid of promised utilities and the discretization of the AR(1) process governing the evolution of z.

Grid for promised utility. Following Menzio and Shi (2010), the lowest and highest values for the grid of promised utilities are set as follows:

$$\underline{x} = \frac{u(b)}{1-\beta} - \varepsilon_x, \quad \overline{x} = \frac{u(f(\overline{y}, \overline{z}))}{1-\beta} + \varepsilon_x$$

The grid of promised utilities is then a grid of N_x points between these two values with spacing parameter spacing_x.

Discretization idiosyncratic firm productivity $\tilde{z}$. This is simply discretized with the method proposed by Rouwenhorst (1995) with N_z points.

Table E.2 summarizes the choices for the numerical parameters.

Parameter	Value	Description
Panel A: numerical parameters for model solution		
N_x	401	Number of points promised utility grid
N_z	29	Number of points idiosyncratic firm TFP
ε_x	1	Value for promised utility grid extrema
spacing_x	1.5	Spacing parameter promised utility grid
Panel B: numerical parameters for model simulation		
T_{sim}	10000	Number of simulated periods
N_{sim}	2000	Number of simulated agents
$T_{\text{dis,sim}}$	1000	Number of periods to discard for moments computation
Panel C: numerical parameters for SMM estimation		
N_{glo}	100	Number of points to evaluate in global stage, estimation $\tilde{z}$
	5000	Number of points to evaluate in global stage, estimation ζ
N_{loc}	10	Number of points to evaluate in local stage, estimation $\tilde{z}$
	20	Number of points to evaluate in local stage, estimation ζ
N_{eco}	5	Number of economies to simulate
T_{cal}	5000	Number of simulated time periods
T_{dis}	500	Number of periods to discard for moments computation
N_{cal}	1500	Number of simulated firms

Table E.2: Numerical parameters.

E.2 Solution procedure

Solving the full model is a very challenging exercise. In each iteration towards the equilibrium - given the current guess - there are four steps to perform: (1) solve for market tightness (2) solve workers' search problem (3) solve for the problem of the unemployed workers (4) solve the problem of the firm and update. I will outline the solution of each subproblem and then lay out the full solution algorithm. Note that, in order to have a good starting guess when solving the full model, I first solve a version of the model without on the job search. The four steps are present in each of the two cases, but I will highlight differences between the solution of the full model and the simpler model in each stage when required.[53]

Step 1: market tightness. Let i indicate the current iteration number and $J^{(\text{i}-1)}$ the current initial guess for the value of the firm. From the free-entry condition (7) we know that in all visited markets the relation must hold with equality, so that, rearranging we can find tightness as follows:

$$\theta^{(\text{i})}(s,x) = q^{-1}\left(\frac{k}{J^{(\text{i}-1)}(s,z_0,x)}\right) \tag{E.1}$$

Thus, for all $s \in S$ and for all $x \in X$:

- compute the ratio $\frac{k}{J^{(\text{i}-1)}(s,z_0,x)}$;
- because $q \in [0,1]$, if the ratio is not in this interval then use complementary slackness and set $\theta^{(\text{i})}(s,x) = 0$;
- otherwise, compute tightness using equation (E.1).

Furthermore, by inserting the obtained values into the function for the job finding probability, I obtain $p^{(\text{i})}(\theta)$. Because it will be needed afterwards, at this step I also compute for all $s \in S$ the exact last market $x^{\text{switch}}(s)$ where it is profitable for firms to post vacancies. This market solves:

$$J(s, z_0, x^{\text{switch}}(s)) = k$$

which I solve with a numerical solver.

Step 2: workers' search problem. Workers' search problem is summarized by the return to search function (3) and its corresponding first order condition (8). There are three relevant intervals for all $s \in S$: (i) for all $x \in [\underline{x}, V]$ the return to search is lower or equal than zero (ii) for all $x \in (V, x^{switch}(s))$ the return to search is strictly positive and strictly concave in x (iii) $x \in [x^{switch}(s), \overline{x}]$ the return to search is zero. Therefore, the solution must be in the interval in (ii) and because of strict concavity the first order condition is necessary and sufficient to characterize the maximum. Thus, for all $s \in S$ and for all $V \in X$:

[53] I will assume that block recursivity holds, so I will replace the aggregate state ψ with s in the description below to ease up the explanation.

- if $V \geq x^{\text{switch}}(s)$ then set $x^{*(\text{i})}(s,V) = V$;
- else, solve with a numerical solver the first order condition (8) with respect to $x^{*(\text{i})}(s,V)$ in the interval $x \in (V, x^{\text{switch}}(s))$;
- insert $x^{*(\text{i})}(s,V)$ into the job finding probability previously computed and into the expression for the return of search to get $\tilde{p}^{(\text{i})}(s,V)$ and $R^{(\text{i})}(s,V)$.[54]

The policy for x^* has to be computed very precisely. However, because the derivative of the job finding probability tends to minus infinity for values of x approaching x^{switch}, and because I do not have a closed form expression for it but rather have to compute it numerically, solving for the FOC close to this point is potentially problematic. To overcome this issue, I approximate[55] the job finding probability p - which is a function of the promised utility values - as follows:

$$a_0 + a_1(V - \underline{x})^2 \tag{E.2}$$

which allows me to compute the derivative in closed form.

Step 3: unemployed workers' problem. Solving the problem of the unemployed amounts to solve the fixed point problem defined by (4). Specifically, using as starting guess for the unemployment value $\underline{x}$, I proceed as follows:

- for all $s \in S$, compute the new guess for the value of unemployment using equation (4);
- if the maximum of the absolute value of difference between the old and new guess is lower than the convergence threshold then define the last obtained value as the solution for the unemployment value $U^{(\text{i})}$;
- otherwise, keep iterating until convergence.

Step 4: firms' problem and updating. The firms' problem can be divided into three substages: (i) finding the optimal promised utilities in each future state of the world (ii) finding the optimal wages (iii) updating the firm value. In the simpler model without on the job search, note that the first order condition with respect to the future promised utility (9) becomes very simple: the right hand side becomes zero due to the lack of search frictions and the optimal policy prescribes constant wages. Therefore $W(\hat{\xi}) = V$ for all V, ξ and, substituting this into the promise keeping constraint I get $V = u(w) + \beta\delta\mathbb{E}\left[U(\hat{\psi})\right] + \beta(1-\delta)V$ which can easily be solved for w for all V, ξ. One can then immediately substitute these optimal policies to get the updated firm value.

The firms' problem with on the job search is instead solved as follows. Let $w^{(\text{i}-1)}$ be the current guess for the wage policy (as starting guess I use the wage policy obtained from the simpler problem without on the job search). Then:

[54] Computing $\tilde{p}$ is not strictly necessary to solve the simpler problem without on the job search.

[55] A similar approximation procedure is used by Balke and Lamadon (2022).

- for all $\xi \in S \times Z$ and all $V \in X$, using the current guess for the wage policy, for all $\hat{\xi} \in S \times Z$ use equation (9) to solve for $W^{(i)}(\hat{\xi})$;
- replace the $W(\hat{\xi})$ obtained into the promise keeping constraint (6), which then can be solved for the new guess for $w^{(i)}$ for all $\xi \in S \times Z$ and all $V \in X$;
- for all $\xi \in S \times Z$ and all $V \in X$ get the new guess of the firm value $J^{(i)}$ with equation (5) using the policies $w^{(i)}$ and $W^{(i)}$ just computed.

The policy for W has to be computed very precisely. However, this is very hard for the same reasons described above for the optimal search choice. Therefore, I follow the same approach as before and approximate $\tilde{p}$ with the functional form E.2, which makes things easier as now I have a closed form expression for the derivative. Finally, because also the new guess for the firm value has to be computed very precisely, I approximate that too with the same functional form E.2, which also allows me to get a smooth version of the updated wage policy $w^{(i)}$ through the envelope condition $-\frac{\partial J}{\partial \hat{V}} = \frac{1}{u'(w)}$, which I use a starting guess for the next iteration.

Solution algorithm.

I. Set initial guesses:
   - for the simple model without on the job search, set the firm value as a strictly concave function of the grid for promised utilities;
   - for the full model set the initial firm value and the initial guess for the wage policy as those obtained from solving the simple model without on the job search;

II. Solve for market tightness as described in Step 1;

III. Solve the workers' search problem as described in Step 2;

IV. Solve the unemployed workers' problem as described in Step 3;

V. Solve the firms' problem and update as described in Step 4;

VI. Compute the difference between the value of the firm from the original guess and the update at all grid points below the last open market. If the maximum - in absolute value - of such difference is lower than the tolerance threshold then exit the loop, otherwise go back to point II with the new updated guesses.

F Estimation

This section describes how I estimate the parameters governing the exogenous stochastic processes not already obtained from closed form expressions described in the calibration section. The numerical parameters chosen for the estimation procedure are reported in Table E.2.

Let θ be the vector of parameters that has to be estimated. θ is chosen to minimize the following objective function:

$$\min_{\theta} \hat{m}(\theta)' W \hat{m}(\theta) \tag{F.1}$$

where $\hat{m}(\theta)$ is a vector of moments that depends on the parameters to be estimated and W is a weighting matrix. The procedure involves a global and a local stage. In the global stage I compute the value of the objective function for N_{glo} combination of points for the elements of the vector θ. The combinations correspond to the first N_{glo} of a Sobol sequence. At the end of the global stage, the best - in the sense of providing the lowest values of the objective function - N_{loc} points pass to the local stage. In the local stage, for each of the N_{loc} points, equation (F.1) is solved for the minimum using the Nelder-Mead algorithm with starting guess each of such points. The minimum is then the vector of parameters among the N_{loc} local points that returns the lowest value of the objective function.

To estimate the parameters governing idiosyncratic firm productivity, I simulate its exogenous process for T_{cal} periods and for N_{cal} firms. I then aggregate the model-generated data at the annual frequency (I take as annual measure the values in the last quarter and I define a year as recessionary if there are at least two consecutive quarters in which the economy is in downturn) and run regression (1) on the simulated data to recover the model-generated shocks ν. Finally, I match the model generated moments and the moments in the data. I discard the first T_{dis} points from moments computation and, in order to smooth the surface of the objective function, I simulate the process for N_{eco} economies and average moments across them. Letting m indicate a generic moment, $\hat{m}(\theta)$ is defined as follows:

$$\hat{m}(\theta) = \frac{m_{\text{data}} - m_{\text{simulated}}(\theta)}{m_{\text{data}}} \tag{F.2}$$

The weighting matrix W is a diagonal unitary matrix when ζ is inactive and otherwise its values related to the share of firms experiencing mass layoffs take the value $0.15/2$, those related to the duration of the disaster state and the share R/NR of firms exiting the disaster state take the value $0.7/2$ and Kelley's skewness takes the value 0.15. The targeted moments are described in detail in Section 4 of the main text.