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July 2024 (updated April 2026)

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Do we need firm data to understand macroeconomic dynamics?*

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Sveriges Riksbank Working Paper Series No.438 — July 15, 2024
Updated Version: April 29, 2026

Abstract

We study the role of heterogeneity in the revenues of individual firms for euro area macro-financial dynamics. To this end, we specify two models: a standard aggregate vector autoregressive model (VAR) and a functional VAR (fVAR) which also incorporates the feedback loop between the firm-level revenue distribution and aggregate variables. Our results demonstrate that the behavior of the firm-level revenue distribution plays a significant role in shaping up the dynamics of key euro area aggregate (macroeconomic and financial) variables.

JEL classification: C11, C32, C52, C54, E22, E32

Keywords: Firm-level revenues, Functional Vector Autoregressions, Heterogeneous Agent Models, Business Cycle fluctuations

*The authors thank Natalia Bailey, Fabio Canova, Stephanie Ettmeier, Jesus Fernandez-Villaverde, Daria Finocchiaro, Domenico Giannone, Mathias Klein, Michael McCracken, Giorgio Primiceri, Tatevik Sekhposyan, Ulf Söderström, Gianluca Violante and several seminar participants for comments. The opinions expressed in this article are the sole responsibility of the authors and should not be interpreted as reflecting the views of Sveriges Riksbank, European Central Bank, the Eurosystem, the CEPR and the CeMoF.

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1 Introduction

Over the last two decades, the macroeconomic literature has progressively moved away from the representative agent paradigm and has delved into the role of "heterogeneity" of economic agents (mainly, households and firms) to explain the transmission mechanism of economic shocks.

A large and growing body of work has found that economic shocks are likely to have distributional implications. For example, recent work has discussed whether the recent large increase in inflation has affected economic inequality (Charalampakis et al., 2022; Curci et al., 2022; Pallotti et al., 2023; Basso et al., 2023) or whether monetary policy is a driver of inequality (Coibion et al., 2017; Colciago et al., 2019; Auclert, 2019; Amberg et al., 2022; McKay and Wolf, 2023; Andersen et al., 2023; Lenza and Slacalek, 2024).

However, much less progress has been made, so far, on the question whether the changes in the distribution of individual economic variables play a role in shaping the macro-financial dynamics, above and beyond what is already incorporated in the dynamics of the aggregate variables themselves. In this paper, we focus on the possible interaction between euro area macroeconomic and financial variables and firm data, and we ask whether individual firm dynamics have explanatory power for macro-financial dynamics.

To assess the informational content of firm data without pre-committing to a specific economic mechanism, we specify a general and flexible (linear) macro-econometric model, which nests a wide range of micro-foundations of aggregate economic dynamics. Specifically, we augment a standard macro-financial vector autoregressive model including consumption, investment, GDP, the unemployment rate, the short-term interest rate, the Harmonised Index of Consumer Prices (HICP) and the most popular measure of euro area financial conditions (the Composite Index of Systemic Stress, CISS in short, developed by Kremer et al., 2012), with the quarterly distribution of European firm-level revenues, over the sample 2000Q1-2023Q4.

In principle, the augmented VAR model has an infinite dimension due to the continuity of the distribution of revenues, so we closely follow Chang et al. (2024) to reduce its dimensionality, at the same time retaining the core features of the firms'distribution. This methodology allows us to assess the interaction between macro and micro dynamics, encompassing the complete spectrum of firm-level revenues rather than focusing merely on specific quantiles of the distribution.[1] We define the model augmented with the firm distribution as fVAR, as Chang et al. (2024), and we define simply as VAR the model including only the macroeconomic aggregates.

[1]For alternative methodologies, see Bjornland et al. (2023), Meeks and Monti (2023) and Marcellino et al. (2024).

Both the VAR and the fVAR models are quite large for the relatively short sample of euro area data at our disposal. For this reason, we follow Bańbura et al. (2010) and we use state-of-the-art Bayesian estimation techniques with informative priors along the lines of Litterman (1979); Doan et al. (1984). We treat the parameters governing the informativeness of the priors as random variables and we draw them from their posterior distribution, as suggested in Giannone et al. (2015) and Lenza and Primiceri (2022).

We conduct two main empirical exercises. First, we estimate the generalized impulse responses (GIRFs) to a "business cycle shock", along the lines of Uhlig (2005); DiCecio and Owyang (2010); Giannone et al. (2019); Del Negro et al. (2020); Angeletos et al. (2020); Cimadomo et al. (2022). This shock provides an accurate description of the dynamic correlations among the variables over the typical cycle and is not meant to capture a specific structural shock. The appeal of this exercise, as in Cimadomo et al. (2022), is that it allows us to draw some insight into the estimated parameters in the VAR and the fVAR. In Vector Autoregressive models, the individual estimated parameters cannot be compared one by one to assess the similarity across models. However, our generalized impulse responses convolve the estimated VAR and fVAR parameters and, thus, comparing GIRFs we are also able to compare the estimated parameters across models. Our results show, first, that both the VAR and the fVAR models estimate generalized impulse responses in line with the view that demand shocks are the main drivers of the business cycle. Remarkably, however, the VAR and the fVAR models exhibit quantitatively substantial differences in the generalized impulse responses to a business cycle shock, systematically across variables. In particular, the response of the aggregate variables in the fVAR model tends to be less persistent.

Chang and Schorfheide (2022) found that augmenting an aggregate VAR model of the US economy with the distribution of household income did not lead to any change in the assessment of the US macroeconomic dynamics. Acharya et al. (2023), Ettmeier (2023), and, to a smaller extent, Bayer et al. (2024) find similar results for the impact of household heterogeneity on the assessment of aggregate dynamics. Our results, instead, suggest that the evolution over time of the distribution of euro area firm-level revenues contains relevant information for aggregate dynamics, above and beyond what is already incorporated in the other macro-financial aggregates in the model.

The fVAR model is larger than the VAR, and our approach to treating the parameters governing the prior tightness also implies that the prior distributions tend to be more informative in the fVAR model. Hence, the just highlighted differences in the parameters across models might also stem from the stronger shrinkage implied by tighter priors in the fVAR. For this reason, we run a second exercise in which we compare the out-of-sample forecasting performance of the models. The idea is that if the parameters in the two models differ only because of the different intensity by which we shrink the parameters toward zero and not also because they draw on different information sets, then the fVAR model should be a worse forecasting model than the VAR. We find that the fVAR model is a better forecasting model than the VAR for most aggregate variables. Hence, we conclude that the euro area firm-level revenue distribution contains information that is relevant to explain macro-financial dynamics in the euro area. All our results are robust to several perturbations of our empirical models. In particular, i) we augment the VAR and the fVAR model with a measure of aggregate firm revenues, ii) we set the overall degree of shrinkage of the Minnesota priors to the same value in the two models, iii) we include more lags than in our benchmark specifications and iv) we replace the prior specification of Giannone et al. (2015) and Lenza and Primiceri (2022) with the priors in Chan (2022), which shrink the parameter on the own lags of the variables differently from those on the lags of the other variables.

Our paper contributes to the ongoing debate about the importance of firm heterogeneity in shaping aggregate dynamics. Numerous studies have highlighted the relevance of heterogeneity in firm financing and its determinants—such as size, leverage, industrial sector, age, and debt maturity structure—in explaining macroeconomic dynamics (Gertler and Gilchrist, 1994; Caballero and Engel, 1999; Cooley and Quadrini, 2006; Covas and Den Haan, 2012; Gilchrist et al., 2014; Arellano et al., 2019; Begenau and Salomao, 2019; Crouzet and Mehrotra, 2020) and the transmission of monetary policy (Jeenas, 2019; Ottonello and Winberry, 2020; Cloyne et al., 2020; Jungherr et al., 2022; Deng and Fang, 2022; Krusell et al., 2023). Some research focusing on capital distribution suggests that its impact on aggregate dynamics and monetary policy is limited (Khan and Thomas, 2008; Kobi and Wolf, 2020; Cao et al., 2024).

Our findings underscore the significant role of the distribution of firm revenues for aggregate dynamics in the euro area. Our results are in line with the idea that the firms' lending capacity is often more closely tied to their earnings than to their collateral (Ivashina et al., 2022; Drechsel, 2022; Caglio et al., 2022).

Our work, leveraging the method developed in Chang et al. (2024), distinguishes itself from other studies utilizing micro-data by offering a direct mapping of the feedback loop between microeconomic variables and aggregate outcomes. Moreover, our analysis offers a more general perspective, compared to previous studies on firms that rely on mechanisms linked to specific structural assumptions.

This paper is organized as follows. Section 2 describes the methodology. Section 3 presents the data and describes our empirical application. Section 4 reports the results. Section 5 concludes.

2 Empirical Framework

In this section, we provide the main intuition underlying the methodology of Chang et al. (2024). We refer the reader to the original paper for a more formal description and the technical details.

Define as X_t an $n \times 1$ vector of euro area macro-financial variables which, in our case, are given by real consumption (C_t), real investment (I_t), GDP (Y_t), the unemployment rate (U_t), the short term interest rate (i_t), the Harmonised Index of Consumer Prices (HICP, P_t) and the Composite Index of Systemic Stress (CISS, fci_t). We define simply as VAR the vector autoregressive model specified by including only these variables. To estimate the potential dynamic feedback loop between macro-financial variables and firm-level revenues, we define the linear functional vector autoregressive model fVAR, by adding the log of the cross-sectional distribution of firms' revenues $\gamma_t(z)$ in the VAR model.

More specifically, $[X_t \ \gamma_t(z))]$ evolves according to the following linear law of motion:

$$\begin{cases} X_t = B_{XX}X_{t-1} + \int B_{X\gamma}(z)\gamma_{t-1}(z)dx + \varepsilon_{X,t} \\ \gamma_t = B_{\gamma X}(z)X_{t-1} + \int B_{\gamma\gamma}(z)\gamma_{t-1}(z)dz + \varepsilon_{\gamma,t}(z) \end{cases} \tag{1}$$

Here, $\varepsilon_{X,t}$, is a random vector with mean zero and covariance Σ_{XX} and $\varepsilon_{\gamma,t}(z)$ is a random element in a Hilbert space with covariance function $\Sigma_{\gamma\gamma}(z)$. Finally, the joint covariance function for $\varepsilon_{X,t}$ and $\varepsilon_{\gamma,t}(z)$ is given by $\Sigma_{\gamma,X}$.

Chang et al. (2024) suggest to tackle the issues posed by the infinite dimension of the fVAR by estimating a K-dimensional specification of the model. This is achieved by approximating the infinite-dimensional distributional dynamics as follows:

$$\gamma_t^{(K)}(x) = \sum_{K=1}^{K} \alpha_{k,t}\eta_k(x) = \begin{bmatrix} \eta_1(x) & \dots & \eta_K(x) \end{bmatrix} \begin{bmatrix} \alpha_{1,t} \\ \vdots \\ \alpha_{K,t} \end{bmatrix} = \eta'(x)\alpha_t \tag{2}$$

where $\begin{bmatrix} \eta_1(x) & \dots & \eta_K(x) \end{bmatrix}$ is a sequence of time-invariant basis functions. Under this approximation for the distribution $\gamma_t(x)$, the infinite dimensional fVAR model can be rewritten as an $n + K$-dimensional model as

$$\begin{bmatrix} X_t \\ \alpha_t \end{bmatrix} = \begin{bmatrix} B_{XX} & B_{X\alpha}\Omega_\alpha \\ B_{\alpha X} & B_{\alpha\alpha}\Omega_\alpha \end{bmatrix} \begin{bmatrix} X_{t-1} \\ \alpha_{t-1} \end{bmatrix} + \begin{bmatrix} u_{X,t} \\ u_{\alpha,t} \end{bmatrix} \tag{3}$$

for suitably defined Ω_α and where the vector of innovations $u_t = \begin{bmatrix} u_{X,t} \\ u_{\alpha,t} \end{bmatrix}$ is assumed to be Gaussian: $u_t \sim N(0, \Sigma)$.

To obtain an estimate of the α_t vector time-series, as in Chang et al. (2024) we define a set of cubic splines as basis for the log density with knots x_k, $k = 1, \ldots, K-1$ and we estimate the $\hat{\alpha}_t$ spline coefficients for $t = 1, \ldots, T$ in a first stage. Given the large number of cross-sectional units in our panel available each quarter, we assume that the estimation error incurred to estimate the true spline coefficients is negligible compared to the other sources of uncertainty in equation 3 and, hence, we treat the latter as a vector autoregressive model for observable variables.[2] Once the model described in equation 3 is estimated, we can use the basis functions described above to convert the model outcomes in terms of spline coefficients (e.g. forecasts and impulse response functions), in the corresponding outcomes for the distribution of firm revenues.

Our fVAR is estimated using the Bayesian techniques described in Giannone et al. (2015) and Lenza and Primiceri (2022). The most noteworthy aspect of the methodology is that we do not impose a specific value on the hyperparameters governing the tightness of the prior distributions, but we treat them as random variables and we conduct posterior inference also on them. The data are stationarized, before entering the vector autoregressive models, and the latter are specified with two lags. The prior distributions for the lag coefficients and error variances are in the Normal-Inverse Wishart class and are parameterized to shrink the model estimates toward the parameters of a random walk model, in the tradition of the Minnesota prior (Litterman, 1979; Doan et al., 1984; Bańbura et al., 2010).[3] Given that our sample spans also the COVID and the post-COVID period, we handle the unprecedented volatility experienced in the euro area macro-financial dynamics as suggested in Lenza and Primiceri (2022).

The Generalized Impulse Responses to the business cycle shocks are estimated as the impulse responses to an exogenous surprise to GDP, obtained by placing GDP first in a Choleski order, similarly to Del Negro et al. (2020); Cimadomo et al. (2022). Del Negro et al. (2020) shows that this simple procedure produces very similar results to those obtained with the more sophisticated schemes described in Uhlig (2005); DiCecio and Owyang (2010); Giannone et al. (2019); Angeletos et al. (2020).

[2]See Chang et al. (2024) for a more general treatment of the estimation problem of the fVAR model when the α_t are considered as unobservable.

[3]The data are stationarized, so we center the priors on all the lag coefficients to zero.

3 Data

We study the joint dynamics of macro-financial aggregates with micro-data on total revenues at the individual firm level. We focus on quarterly observations for the Euro-area, covering a period from the first quarter of 2000 until the fourth quarter of 2023. As mentioned above, the set of aggregate variables we include in our final model is given by: real GDP, aggregate consumption, aggregate investment, the unemployment rate, HICP, the short-term nominal interest rate and the CISS.

For what concerns the individual firm data, we collect quarterly observations on total revenues from Capital IQ Premium (*CIQ hereafter*), a market intelligence platform designed by Standard & Poor's (S&P Global). The platform, at least in its basic version, is widely used in many areas of corporate finance, including investment banking, equity research, and asset management. We make use of the Premium version, providing global standardized financial statements over 17 industries[4] for a total of 825,000 companies, including 13,000 private companies with public debt.[5]

Sample Selection We include in our sample all non-financial corporations reported in the CIQ platform with non-missing information on total revenues for the euro area countries. CIQ reports only firms with revenues equal to or exceeding the amount of one million euros. The final sample includes about 6.3 million observations over the period 2000q1-2023q4.

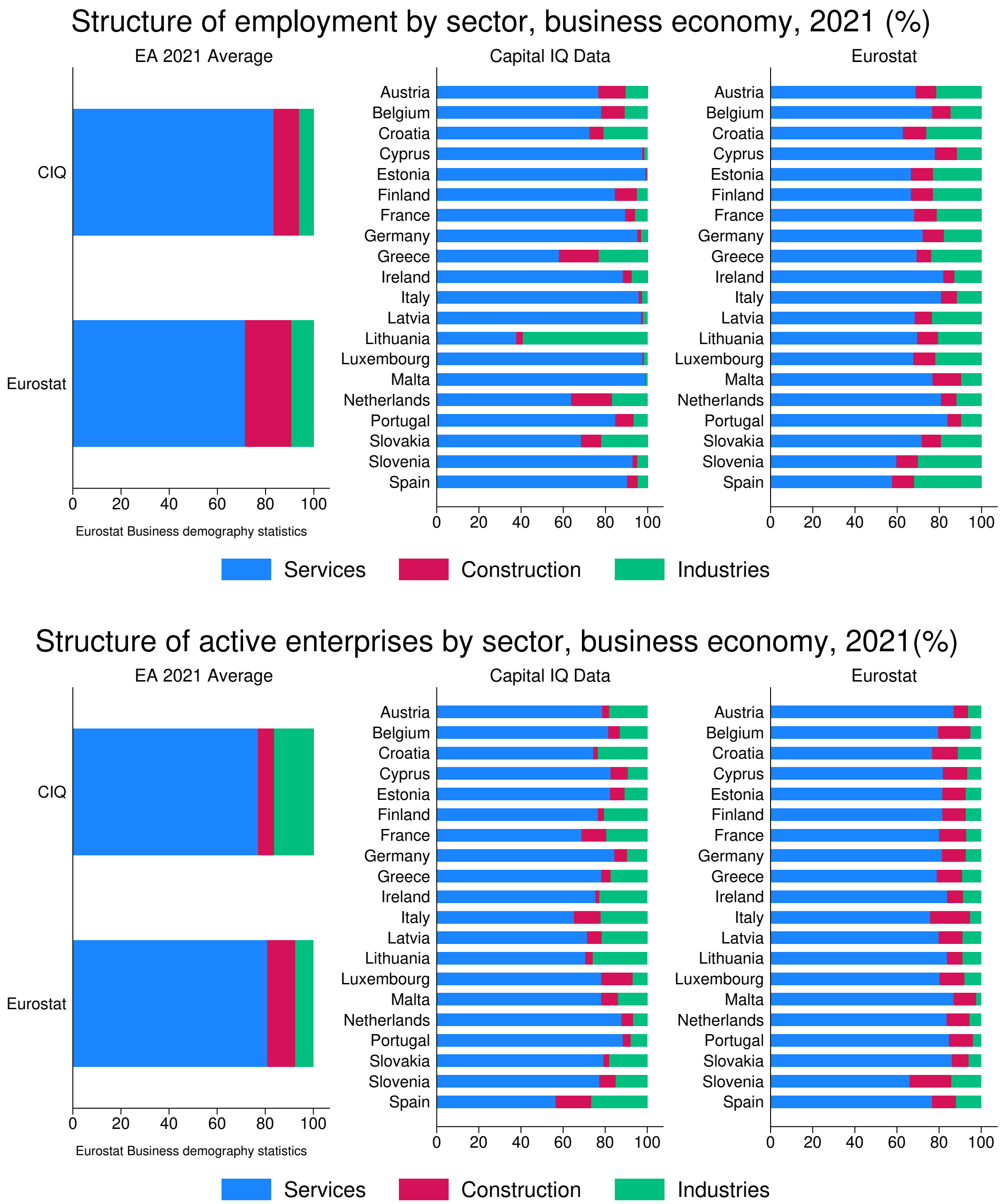
Representativeness of our sample Kalemli-Ozcan et al. (2022) provides guidelines on how to construct representative firm data with ORBIS. We follow their guidelines to assess the representativeness of our sample.

First, in figure 1, top panel, we compare the shares of employment in the euro area countries for three macro-sectors (Service, Construction, and the remaining industries) in our database with the corresponding share available in the Eurostat Business demographic statistics. In the bottom panel, we perform the same comparison for the shares of active firms. For brevity, we only report the comparison for 2021.

[4]Airlines, Asset Management, Banks, Health Care, Homebuilders, Hotels & Gaming, Insurance, Internet Media, Managed Care, Metals & Mining, Oil & Gas, Pharmaceuticals & Biotech, REITs, Restaurants, Retail, Semiconductors, and Telecommunications, Cable & Wireless.

[5]S&P Global collects officially disclosed balance-sheet information from all publicly available sources including regulatory agencies, company websites, exchange websites, and news agencies. Data from private companies are acquired by three third parties: Dun & Bradstreet, Creditsafe, and KLCA. Once collected, these "as-reported" financial data are processed into detailed and traceable charts of accounts consistent with S&P Global data quality standards. Additional information on how data are processed and how to purchase them are provided on the S&PGlobal's website.

Figure 1: Shares of employment and active firms

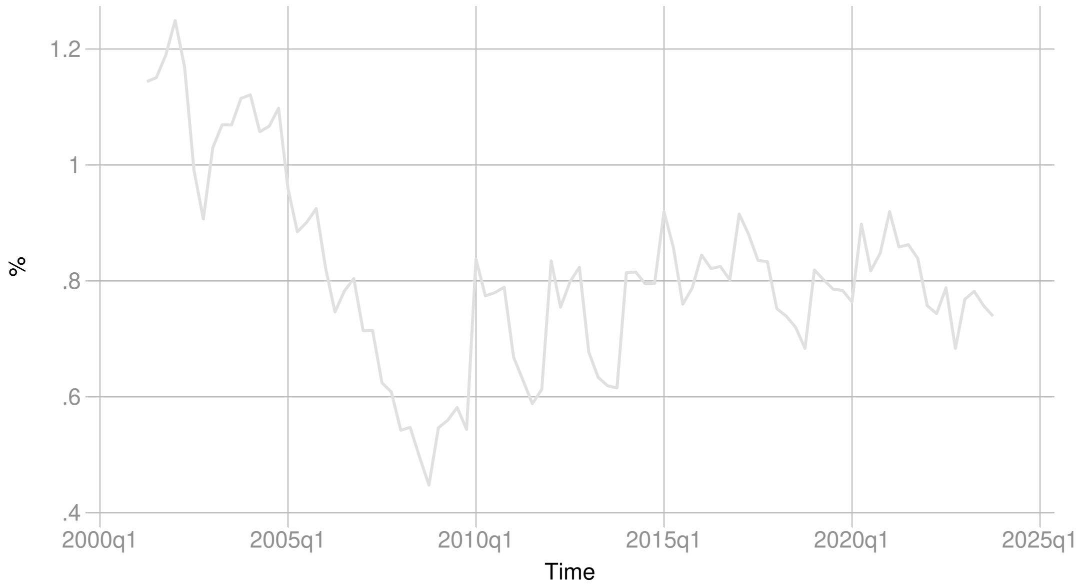


The figure shows that our sample mirrors quite well the shares of employment and active firms reported by Eurostat, across all countries. The only noteworthy feature is a slight under-representation of the construction sector.

Second, in figure 2, we report the ratio of total revenues in CIQ with an aggregate proxy from

Eurostat, based on operating surplus and mixed income from all nonfinancial corporations.

Figure 2: Ratio of total revenues in CIQ and Eurostat counterpart



Coverage ratio = Tot Revenues CIQ / GVA Eurostat

The figure shows that the ratio oscillated between 120% and 70% for a large part of the sample. The values larger than 100% for the ratio at the beginning of the sample indicate that the aggregate proxy for our revenues is indicative but it is not a perfect aggregate match for the micro-economic counterpart.

Data Treatment In the remainder of this paper, we standardize firm-level revenues by Gross Value Added (GVA). Taking this ratio helps to remove the common trend present in micro-data. Moreover, we follow Chang et al. (2024) and we apply an inverse hyperbolic sine transformation to the firm revenues $x_i = g(rev_i)$, given by:

$$x_i = g(rev_i|\varphi) = \frac{log(rev_i + (\varphi^2 rev_i^2 + 1)^{1/2})}{\varphi} = \frac{sinh^{-1}(\varphi rev_i)}{\varphi}$$

with $\varphi = 1$, and $rev_i = (Firm\ i\ revenues)/GVA$.

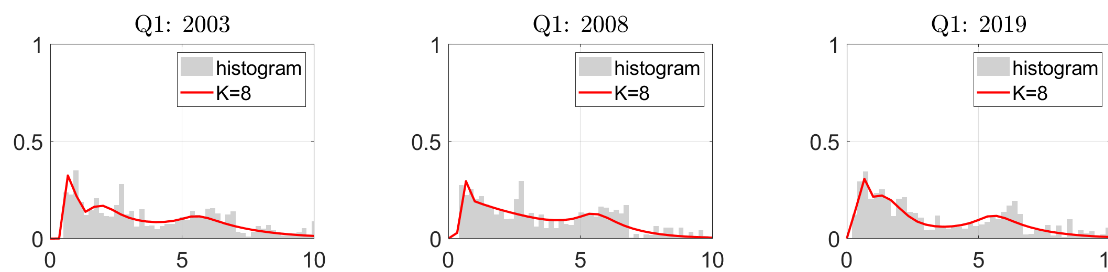
4 Empirical Results

This section describes our main empirical results. First, we show how we approximate the distributions of firm-level revenues. Then, we present the evidence on the feedback loop between macro-financial aggregates and firm-level revenues.

4.1 Cross-sectional densities

In Figure 3, we show for three different quarters in our sample (2003Q1, 2008Q1, and 2019Q1) the empirical densities of the revenues to GVA ratios (grey bars) and the re-constructed densities which we obtain by using eight basis functions (solid red line).

Figure 3: Cross-sectional distributions of revenues to GVA ratio

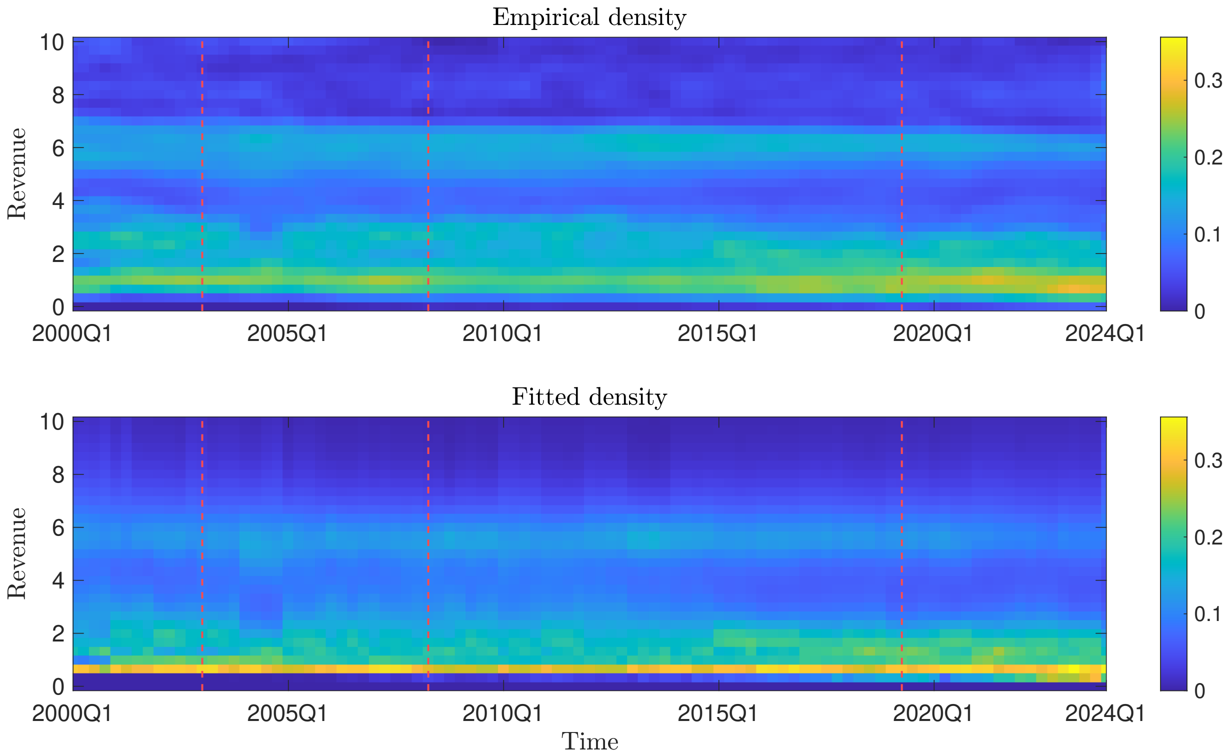


Notes: Grey Bars: histogram of the empirical Total Revenue/GVA distribution; Red Line: log-spline density estimates for $K = 8$ at different points in time.

K=8 is our baseline choice and we note from figure 3 that eight basis functions capture most of the essential features of the distributions.[6] Figure 4 shows, in the form of heatmaps, the full time series of the densities of firm-level revenues (top panel) and the fit we obtain by means of eight basis functions (bottom panel). The three vertical bars in the heatmaps correspond to the three dates in figure 3.

[6]We justify our choice of K=8 on the ground of out-of-sample forecasting accuracy, see section 4.3.

Figure 4: Empirical and fitted revenue distributions over time.



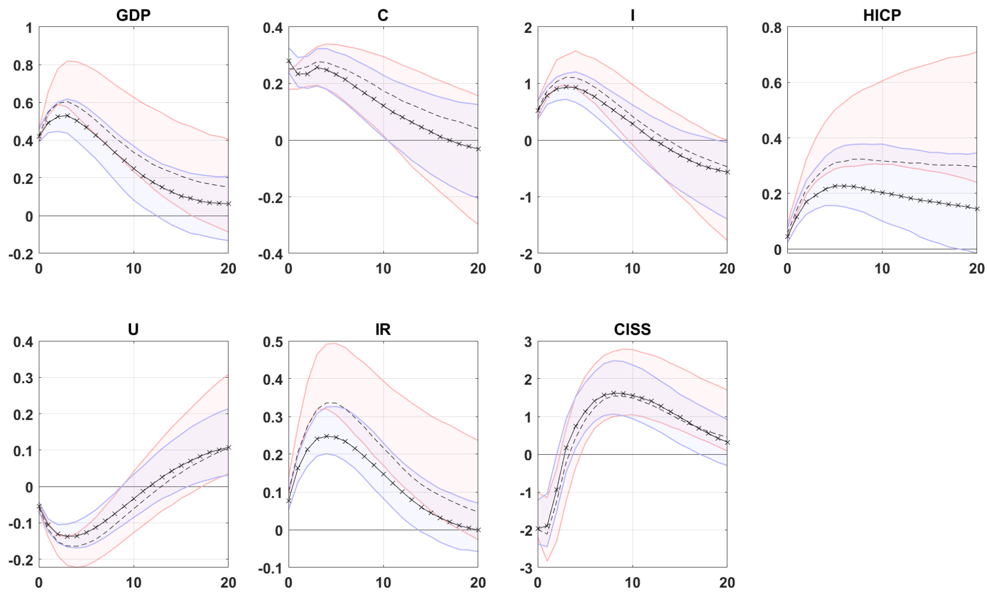
Notes: The figure compares the empirical distribution of firm revenues (top panel) with the fitted distribution (bottom panel), over the sample 2000Q1 - 2023Q4 (horizontal line). Vertical dashed lines indicate sample periods used in Figure 3.

4.2 Generalized Impulse Responses to business cycle shocks

Figure 5 shows the generalized impulse responses of the aggregate variables for the VAR (red areas) and the fVAR (K=8, blue areas) models. We also show the median fVAR results for the K=6 (dashed black line) and K=10 case (solid black line with crosses). The figure reports the responses of the (log-)levels for the different variables.

The generalized impulse responses in the fVAR and the VAR present the same qualitative features. Namely, in the "typical" boom, GDP increases for about a year, and so do also real consumption and investment. The unemployment rate decreases quite persistently, reflecting the typically lagging dynamics of the labor market to the business cycle. The persistent increase in consumer prices suggests that the business cycle fluctuations in the euro area are dominated by demand-type shocks, as in the US (see, for example, Del Negro et al., 2020). The responses of the short-term interest rates reflect the attempt of monetary policy to stabilize the economy. The financial conditions associated with a business cycle boom are initially looser, but they tighten as

Figure 5: Generalized Impulse Responses to a Business Cycle Shock



Notes: **Blue Area**: fVAR, K=8; **Red Area**: aggregate VAR; Dashed line: fVAR median, K=6; Solid line with crosses: fVAR median, K=10. Notice that all IRFs are normalized to have the same median GDP response as the VAR model.

monetary policy becomes tighter over time,

Remarkably, the GIRFs in the fVAR and the VAR are quantitatively quite different. Specifically, the fVAR suggests that the responses of the aggregate variables are attenuated and less persistent than in the VAR. In other words, the inclusion of the cross-sectional distribution of firm revenues in the fVAR has led to a noticeable change in the assessment of the economic dynamics for the euro area aggregate variables.

Chang and Schorfheide (2022) found that including the cross-sectional distribution of household income led to negligible changes in the dynamics of the US aggregate variables. Our results suggest that firms' micro-data are relevant to better describe macroeconomic dynamics. Notice also that the medians of the fVAR models with K=6 and K=10 lead to a similar conclusion, suggesting that our results are robust to the choice of the number of basis functions.

4.3 Out-of-sample forecasting accuracy of the fVAR and the VAR models

Our baseline fVAR with K=8 includes 15 variables, while the VAR includes seven variables. For a relatively small sample, such as ours, the increase in the dimension of the fVAR model compared to the VAR model may lead to sensibly tighter priors. This could suggest that the different GIRFs across models simply reflect a stronger degree of shrinkage toward zero affecting the GIRFs of the fVAR. In our final exercise, we conduct an out-of-sample exercise, comparing the fVAR and the VAR in terms of their ability to forecast the aggregate variables, at the horizon of one quarter ahead. If the difference in GIRFs across the VAR and the fVAR model reflects only a stronger degree of shrinkage of the latter, we would expect the forecasting performance of the fVAR to be worse than that of the VAR.

Table 1 reports the results for the evaluation samples ranging from 2010Q1 to 2023Q4, for all aggregate variables. For each choice of the number of basis functions K (first column, ranging from four to ten), we report the results for the evaluation sample excluding the turbulent 2020 year (top rows, indicated with an asterisk), in which some of the target variables were affected by unprecedented volatility and others, such as inflation, were barely affected, and for the full sample including 2020 (bottom rows). The results are cast in terms of the relative mean squared error of the VAR relative to the fVAR, and a number smaller than one indicates that the fVAR is more accurate than the VAR. The last column reports the average relative MSE across variables in the evaluation sample excluding the year 2020, which we use in order to select the model with the best overall forecasting performance.

The results in Table 1 suggest that the fVAR is often either similar or more accurate than the VAR model. The analysis of the forecast accuracy also shows that the fVAR with K=8 achieves in general the best overall forecasting performance, across variables and evaluation samples. Hence, we conclude that the different GIRFs across the VAR and the fVAR models do not reflect simply the stronger degree of shrinkage impressed on the fVAR model and that the fVAR captures information that is relevant to macro-financial dynamics which is potentially omitted in the VAR.[7]

[7] The two evaluation samples we analyze provide similar results for most variables. The three notable exceptions are inflation, the interest rates and unemployment. For the former two variables, some specifications of the fVAR are even more accurate in relative terms when 2020 is included in the assessment, while the opposite holds for unemployment. These findings are almost entirely due to the outcomes of 2020Q2, in which GDP dropped by an unprecedented amount, while inflation, the nominal interest rates and the unemployment rate remained relatively stable. The stability of inflation and the nominal interest rate is at odds with the economic relationships embedded in most macroeconomic models, such as the Phillips Curve, and it turns out to damage in particular the performance of the VAR model, compared to the fVAR model, while the opposite holds for the unemployment rate, which remained stable during 2020 due to the labor market policies implemented in the euro area. We prefer to rely on the sample excluding 2020 as the baseline sample to select our models, to avoid putting too much weight on one specific quarter of unprecedented volatility for the sake of our model specification.

Table 1: Relative Mean Squared Error

N. of Basis Fcts.	Evaluation Sample	Y_t	C_t	I_t	P_t	U_t	i_t	fci_t	Average
K=4	2010-2023*	0.97	0.97	0.97	1.08	1.02	1.23	0.80	1.01
	2010-2023	0.91	0.96	0.99	0.74	1.37	1.29	0.57	
K=6	2010-2023*	0.94	0.98	0.99	0.94	0.91	1.17	0.77	0.96
	2010-2023	0.93	0.97	1.04	0.75	1.22	1.27	0.62	
K=8	2010-2023*	0.84	0.96	0.96	0.92	0.88	1.16	0.79	**0.93**
	2010-2023	0.87	0.98	0.96	0.58	1.17	1.03	0.72	
K=10	2010-2023*	0.90	0.95	1.04	0.87	0.78	1.46	0.64	0.95
	2010-2023	0.86	0.97	1.00	0.51	1.18	1.08	0.93	

Note: Forecasting horizon: one quarter ahead. Values smaller than one indicate that the fVAR model is more accurate than the VAR. (*) Indicates that we exclude the year 2020 from the evaluation sample. The last column reports the average relative MSE across variables, for the evaluation sample excluding 2020. Macroeconomic variables: GDP (Y_t), real consumption (C_t), real investment (I_t), Harmonised Index of Consumer Prices (HICP) (P_t), unemployment rate (U_t), short term interest rate (i_t), CISS (fci_t).

4.4 Robustness checks

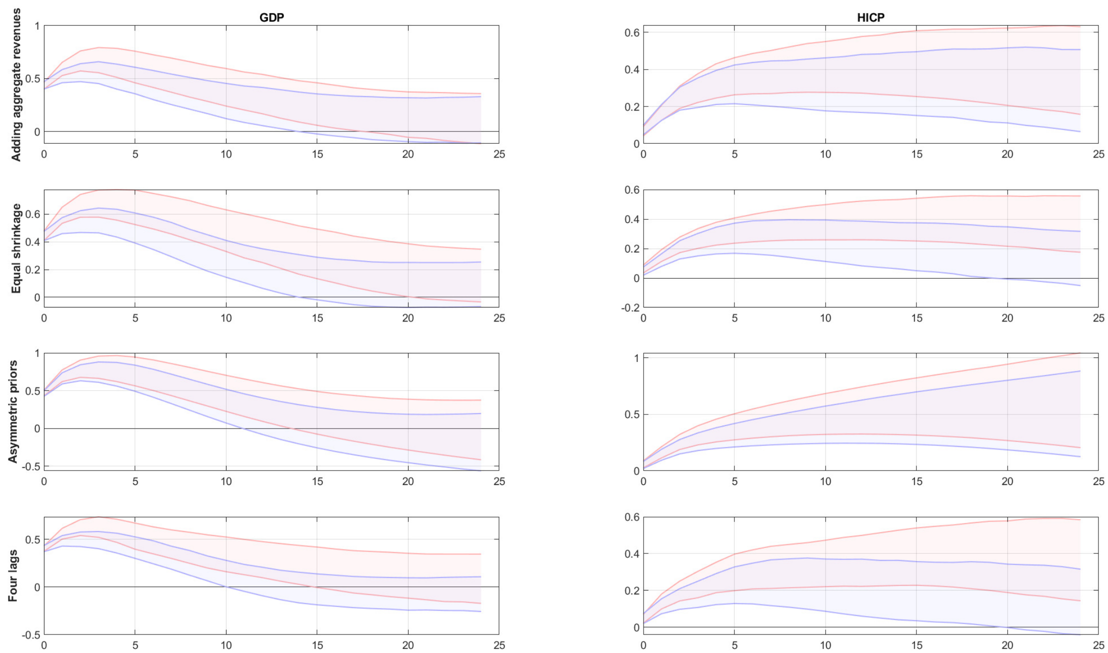
Figure 6 reports the results of four robustness checks we performed on the comparison of generalized impulse responses in the VAR and fVAR models. The left panels refer to GDP and the right panels refer to HICP, for the VAR and fVAR (K=8) models. In the first row, we check if our results are robust to adding a measure of aggregate firm revenues, i.e. the median growth rate of firm revenues, in the VAR and fVAR models.[8] The second row presents another way to assess the (lack of) relevance of the different degrees of shrinkage in the VAR and fVAR. In particular, we compare the VAR and the fVAR (K=8) models in which we have set the degree of shrinkage to be the same in the two models.[9] The third row presents results in which we use the asymmetric priors of Chan (2022), as in Chang et al. (2024) rather than the priors of Giannone et al. (2015). The priors in Chan (2022) shrink the parameter on the own lags of the variables differently from those on the lags of the other variables in the VAR and the degree of shrinkage is

[8]The results with mean growth rates are the same and are not reported here, for brevity

[9]Specifically, we set the parameter governing the overall tightness of the Minnesota prior to 0.2, which is the value traditionally used in macroeconometric studies as suggested in Giannone et al. (2015); Lenza and Primiceri (2022).

set by maximizing the marginal likelihood.[10] Finally, the fourth row presents results from models with four lags, instead of our baseline specification with two lags.

Figure 6: Robustness checks



Notes: Left Panels: GDP. Right Panels: HICP. Blue Area: fVAR, K=8; Red Area: aggregate VAR. Notice that all IRFs are normalized to have the same median GDP response as the VAR model. First row: comparison between VAR and fVAR models both including median firm revenues growth. Second row: comparison between VAR and fVAR models with the same degree of shrinkage. Third row: comparison between VAR and fVAR models with asymmetric shrinkage. Fourth row: comparison between VAR and fVAR models with four lags.

As it is clear from the figure, our main results are robust to the perturbations analyzed in figure 6.[11]

5 Conclusion

In this paper, we follow the insight in Chang et al. (2024) to include micro-data together with macro-financial aggregates in VAR models.

We ask the question of whether aggregate dynamics in the euro area are better captured in a VAR model including exclusively macro-financial aggregates or in a fVAR model including also

[10]Notice that for this robustness check we estimate the model only until 2019Q4, to avoid the excessive volatility experienced during the pandemic.

[11]For the sake of brevity, we report only the results for HICP and GDP.

information on the development of the distribution of firm-level revenues over time.

We find that firm-level data contain information that is relevant to capture euro area aggregate dynamics. We conclude that firm heterogeneity is an important feature to consider in theoretical and empirical business cycle models.

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