SVERIGES RIKSBANK
WORKING PAPER SERIES

438

Do we need firm data to understand macroeconomic dynamics?

Michele Lenza and Ettore Savoia

July 2024

WORKING PAPERS ARE OBTAINABLE FROM

www.riksbank.se/en/research
Sveriges Riksbank • SE-103 37 Stockholm
Fax international: +46 8 21 05 31
Telephone international: +46 8 787 00 00

Do we need firm data to understand macroeconomic dynamics?*

Michele Lenza
European Central Bank and CEPR

Ettore Savoia
Sveriges Riksbank and CeMoF

Sveriges Riksbank Working Paper Series
No. 438, July 2024

Abstract

We study the role of heterogeneity in the revenues of individual firms for euro area macroeconomic dynamics. To this end, we specify two models: a standard aggregate vector autoregressive model (VAR) and an "heterogeneous VAR" (HVAR). The VAR model includes only aggregate data, while the HVAR model also incorporates the feedback loop between firms' revenue distribution and aggregate variables. Our results demonstrate that the behavior of firms' revenue distribution plays a significant role in explaining the dynamics of key euro area macroeconomic variables.

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

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

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.

*The authors thank Natalia Bailey, Fabio Canova, Stephanie Ettmeier, Michael McCracken, Daria Finocchiaro, Mathias Klein, Giorgio Primiceri, Tatevik Sekhposyan, Ulf Söderström 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.
Contact authors: Michele Lenza: michele.lenza@ecb.europa.eu; Ettore Savoia: ettore.savoia@riksbank.se.

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 whether the changes in the distribution of individual economic variables play a role in shaping the macroeconomic 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 variables and firm data, and we ask whether individual firm dynamics have explanatory power for macroeconomic 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 macroeconomic vector autoregressive model including consumption, investment, GDP, the unemployment rate, the short-term interest rate, and the Harmonised Index of Consumer Prices (HICP), with the quarterly distribution of European firms'revenues, over the sample 2000Q1-2023Q4. We define the model augmented with the firm distribution as Heterogeneous VAR (HVAR, hereafter) and we define simply as VAR the benchmark model including only the macroeconomic aggregates.

In principle, the HVAR 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 firms' revenues rather than focusing merely on specific quantiles of the distribution.

Both the aggregate VAR and the HVAR 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 should account for a considerable share of the business cycle fluctuations of the main euro area macroeconomic aggregates and is not meant to capture a specific structural shock. Rather, it provides an accurate description of the dynamic correlations among the variables over the typical cycle. 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 HVAR. Indeed, 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 HVAR parameters and, thus, comparing GIRFs we are also effectively able to compare the estimated parameters across models. Our results show, first, that both the VAR and the HVAR 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 HVAR models exhibit quantitatively substantial differences in the generalized impulse responses to a business cycle shock, systematically across variables. In particular, the response of the macroeconomic variables in the HVAR 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 revenues contains relevant information for aggregate dynamics, above and beyond what is already incorporated in the other macroeconomic aggregates in the model.

The HVAR 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 HVAR model. Hence, the just highlighted differences in the parameters across models might also stem from the stronger shrinkage implied by tighter priors in the HVAR. 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 HVAR model would be a worse forecasting model than the VAR. We find that the HVAR model is a better forecasting model than the VAR for most macroeconomic variables. Hence, we conclude that the euro area firms' revenue distribution contains information that is relevant to explaining macroeconomic dynamics in the euro area. All our results are robust to augment the VAR and the HVAR model with a measure of aggregate firm revenues and to set the overall degree of shrinkage of the Minnesota priors to the same value in the two models.

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) 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 suggested in 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 macroeconomic 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), and the Harmonised Index of Consumer Prices (HICP) (P_t). We define simply as VAR the vector autoregressive model specified by including only these variables. To estimate the potential dynamic feedback loop between macroeconomic variables and individual firms' revenues, we define the linear functional vector autoregressive model HVAR, 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 tackling the issue posed by the infinite dimension of the functional model by estimating a K-dimensional specification of the model. This is achieved by approximating the infinite-dimensional distributional dynamics as follows:

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

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 $\gamma_t(z)$, the infinite dimensional HVAR 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, $k = 1, \dots, K-1$ and we estimate the $\hat{\alpha}_t$ spline coefficients for $t = 1, \dots, T$ 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 for the other sources of uncertainty in equation 3 and, hence, we treat the latter as a vector autoregressive model for observable variables.[1] 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, such as forecasts and impulse response functions, in the corresponding outcomes for the distribution of firm revenues.

Our HVAR 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.[2] 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 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 macroeconomic 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).

3 Data

We study the joint dynamics of macroeconomic aggregates with microdata 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, and the short-term nominal interest rate.

For what concerns the individual firm data, we collect quarterly observations on total revenues

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

[2] Our results are robust to choosing four lags.

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

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 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.

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.

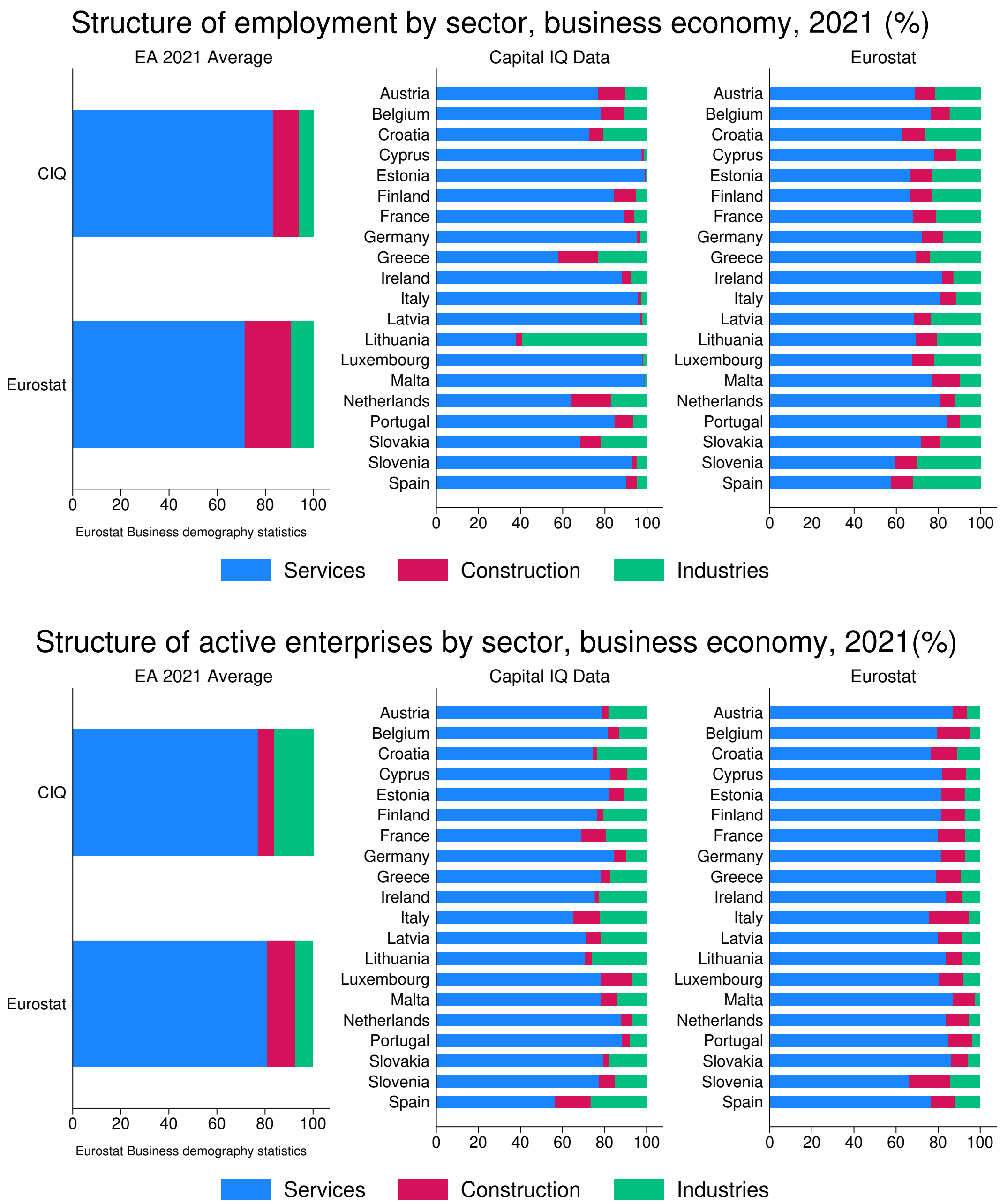
Second, in figure 2, we report the ratio of total revenues in CIQ with an aggregate proxy from Eurostat, based on operating surplus and mixed income from all nonfinancial corporations.

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

[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.

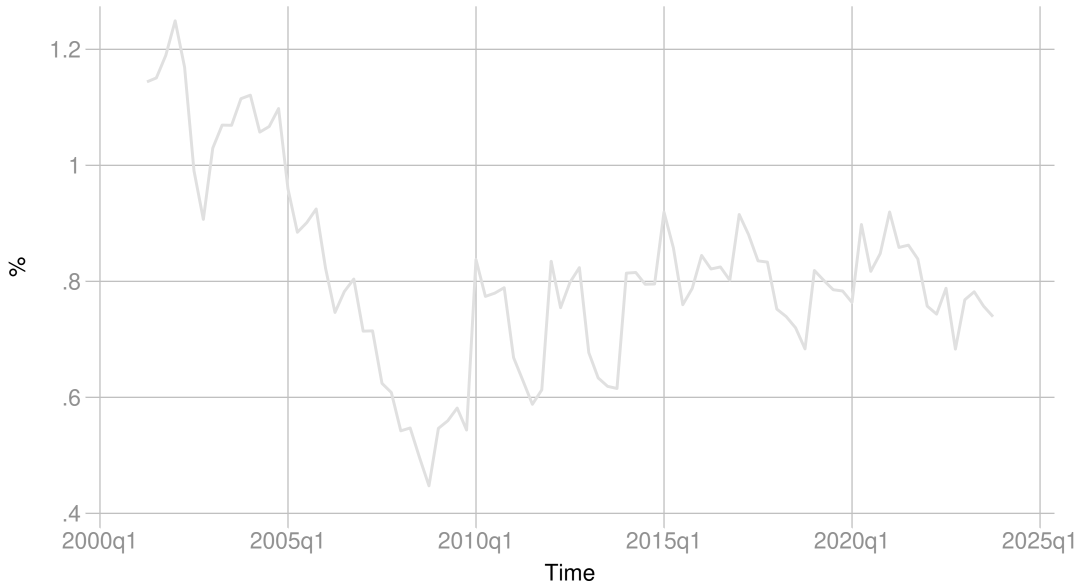
Figure 1: Shares of employment and active firms



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.

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



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 $rev_i = (Firm\ i\ revenues)/GVA$.

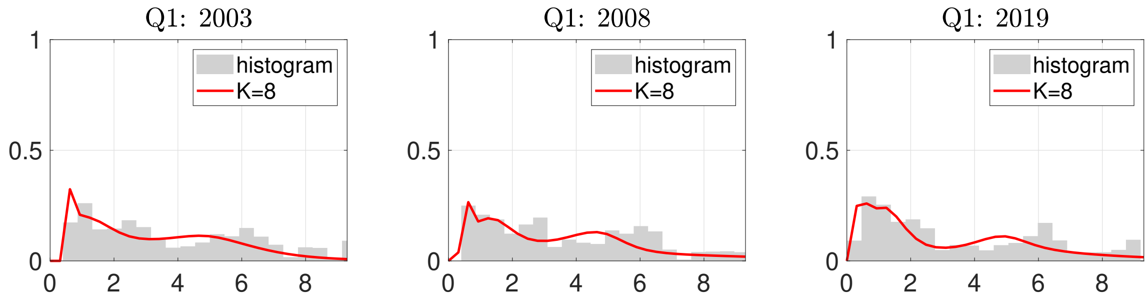
4 Empirical Results

This section describes our main empirical results. First, we show how we approximate the distributions of firm revenues. Then, we present the evidence of the feedback loop between macroeconomic aggregates and firms' 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]

4.2 Generalized Impulse Responses to business cycle shocks

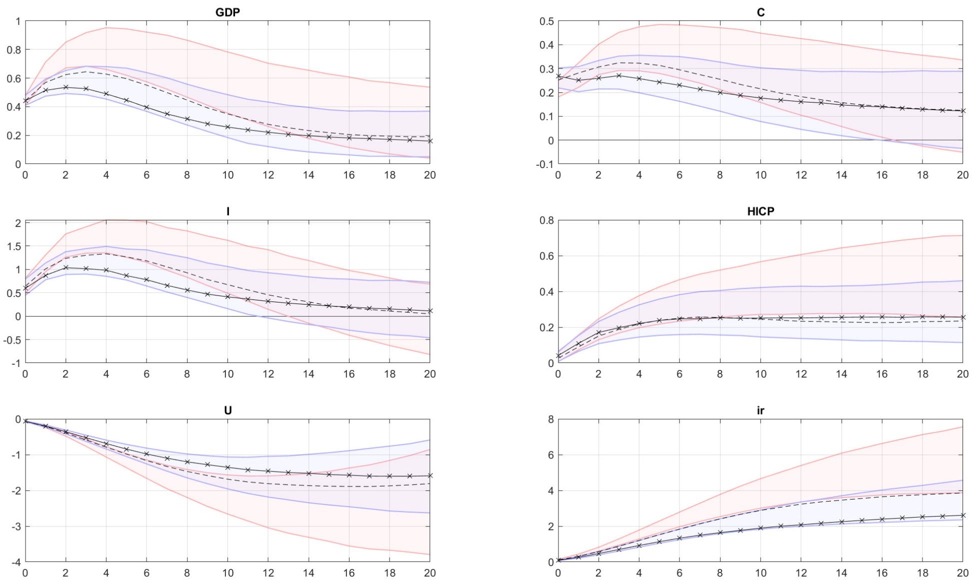
Figure 4 shows the generalized impulse responses of the aggregate variables for the VAR (red areas) and the HVAR (K=8, blue areas) models. We also show the median HVAR results for the K=6 (dashed black line) and K=10 case (solid black line with crosses). The figure reports the responses of the (log-)levels for the different variables.

The generalized impulse responses in the HVAR 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 it is for the US (see, for example, Del Negro et al., 2020). Finally, the responses of the short-term interest rates reflect the attempt of monetary policy to stabilize the economy.

Remarkably, the GIRFs in the HVAR and the VAR are quantitatively quite different. Specifically, the HVAR 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

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

Figure 4: Generalized Impulse Responses to a Business Cycle Shock



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

in the HVAR 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 HVAR models with K=6 and K=10 lead to a similar conclusion, suggesting that our results are quite robust to the choice of the number of basis functions.

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

Our baseline HVAR with K=8 includes 14 variables, while the VAR includes six variables. For a relatively small sample, such as ours, the increase in the dimension of the HVAR model compared to the VAR model may lead to sensibly tighter priors. This could raise the doubt that the different GIRFs across models simply reflect a stronger degree of shrinkage toward zero affecting the GIRFs of the HVAR. In our final exercise, we conduct an out-of-sample exercise, comparing the HVAR 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 HVAR model reflects only a stronger degree of shrinkage of the latter, we would expect the forecasting performance of the HVAR 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 HVAR, and a number smaller than one indicates that the HVAR 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.

Table 1: Relative Mean Squared Error

N. of Basis Fcts.	**Evaluation Sample**	Y_t	C_t	I_t	P_t	U_t	i_t	**Average**
K=4	2010-2023*	0.96	0.93	0.90	1.06	1.22	1.47	1.09
	2010-2023	0.90	0.93	0.91	0.76	1.41	1.35	
K=6	2010-2023*	0.91	0.94	0.89	0.91	1.07	1.46	1.03
	2010-2023	0.94	0.96	0.94	0.71	1.27	1.38	
K=8	2010-2023*	0.77	0.87	0.79	1.04	0.90	0.91	**0.88**
	2010-2023	0.77	0.90	0.77	0.78	0.98	0.67	
K=10	2010-2023*	0.76	0.86	0.88	1.07	0.83	1.05	0.91
	2010-2023	0.75	0.90	0.78	0.64	0.98	0.73	

Note: Forecasting horizon: one quarter ahead. Values smaller than one indicate that the HVAR 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).

The results in Table 1 suggest that the HVAR is often either similar or more accurate than the VAR model, especially for the GDP components and consumer prices. The analysis of the forecast accuracy also shows that the HVAR 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 HVAR models do not reflect simply the stronger degree of shrinkage impressed on the HVAR model and that the HVAR captures information that is relevant to macroeconomic dynamics which is potentially omitted in the VAR.[7]

4.4 Robustness checks

Figure 5 reports the results of two robustness checks we performed on the comparison of generalized impulse responses in the VAR and HVAR models. Namely, the left panels report the results for GDP (top panel) and HICP (bottom panel) for VAR and HVAR (K=8) models adding a measure of aggregate firm revenues, i.e. the median growth rate of firm revenues[8]. The right panels, instead, present another way to assess the (lack of) relevance of the different degrees of shrinkage in the VAR and HVAR. In particular, we compare the VAR and the HVAR (K=8) models in which we have set the degree of shrinkage to be the same in the two models.[9]

As it is clear from the figure, our main results are barely affected in the two robustness checks.[10]

5 Conclusion

In this paper, we follow the insight in Chang et al. (2024) to include micro-data together with macroeconomic 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 macroeconomic aggregates or in an HVAR model including also

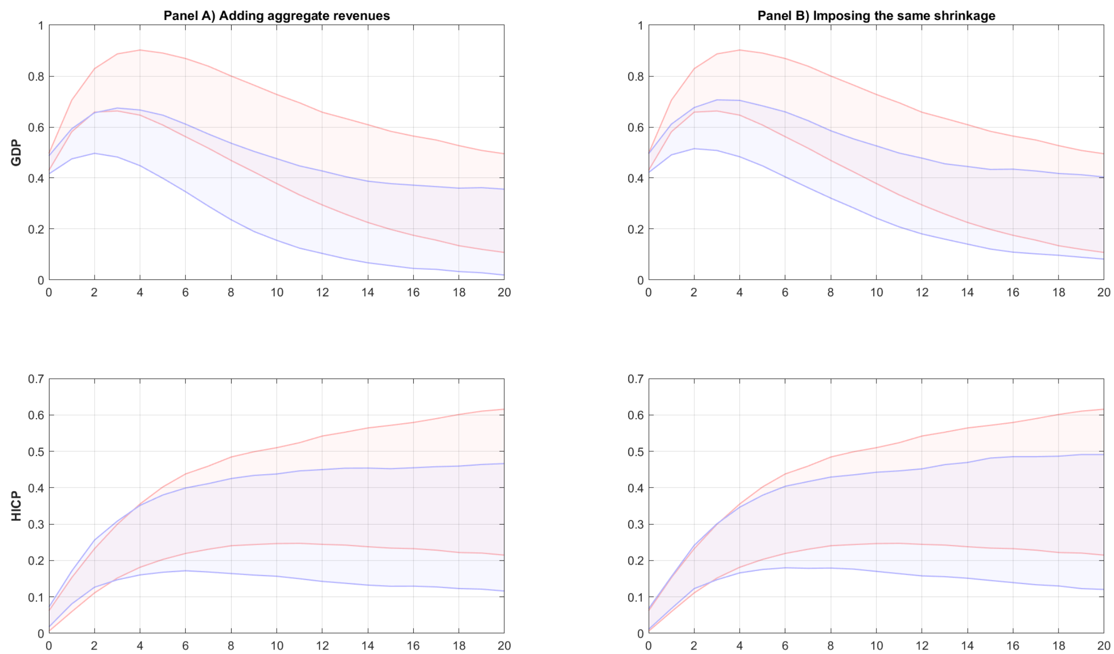
[7]The two evaluation samples we analyze provide similar results for most variables. The two notable exceptions are inflation and the interest rates for which some specifications of the HVAR are even more accurate in relative terms when 2020 is included in the assessment. This finding is almost entirely due to the outcomes of 2020Q2, in which real variables dropped by an unprecedented amount, while inflation and the nominal interest rates remained stable. This 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 HVAR model. While it is possible that the HVAR model is genuinely more accurate than the VAR to capture the complex economic dynamics witnessed during the COVID times, we prefer to rely on the sample excluding 2020 to select our models, to avoid putting too much weight on one specific quarter of unprecedented volatility for our model specification.

[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).

[10]For the sake of brevity, we report only the results for HICP and GDP and we focus on the GIRF exercise, but also the results in terms of other variables and out-of-sample performance are barely affected and are available on demand.

Figure 5: Robustness checks



Notes: .Left Panel: comparison between VAR and HVAR models both including median firm revenues growth. Right Panel: comparison between VAR and HVAR models with the same degree of shrinkage. Top panels: GDP. Bottom Panels: HICP. Blue Area: HVAR, K=8; Red Area: aggregate VAR. Notice that all IRFs are normalized to have the same median GDP response as the VAR model.

information on the development of individual revenues over time.

We find that individual firms' data contain information that is relevant to capturing euro area aggregate dynamics. Our results suggest that firm heterogeneity is an important feature to consider in theoretical and empirical business cycle models.

References

Acharya, Sushant, William Chen, Marco Del Negro et al. (2023) "Estimating HANK for Central Banks," Staff Reports 1071, Federal Reserve Bank of New York, 10.59576/sr.1071.

Amberg, Niklas, Thomas Jansson, Mathias Klein, and Anna Rogantini Picco (2022) "Five Facts about the Distributional Income Effects of Monetary Policy Shocks," *American Economic Review: Insights*, 4 (3), 289–304, 10.1257/aeri.20210262.

Andersen, A., N. Johannesen, M. Jørgensen, and J-L. Peydro (2023) "Monetary Policy and Inequality," *The Journal of Finance*, 78 (5), 2945–2989, https://doi.org/10.1111/jofi.13262.

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas (2020) "Business-Cycle Anatomy," *American Economic Review*, 110 (10), 3030–3070, 10.1257/aer.20181174.

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe (2019) "Financial Frictions and Fluctuations in Volatility," *Journal of Political Economy*, 127 (5), 2049–2103.

Auclert, Adrien (2019) "Monetary Policy and the Redistribution Channel," *American Economic Review*, 109 (6), 2333–2367.

Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin (2010) "Large Bayesian Vector Auto Regressions," *Journal of Applied Econometrics*, 25 (1), 71–92.

Basso, Henrique S., Olga Dimakou, and Myroslav Pidkuyko (2023) "How Inflation Varies Across Spanish Households," Occasional Papers 2307, Banco de España, Madrid.

Bayer, Christian, Benjamin Born, and Ralph Luetticke (2024) "Shocks, Frictions, and Inequality in US Business Cycles," *American Economic Review*, 114 (5), 1211–1247, 10.1257/aer.20201875.

Begenau, Juliane and Juliana Salomao (2019) "Firm Financing over the Business Cycle," *The Review of Financial Studies*, 32 (4), 1235–1274.

Caballero, Ricardo J. and Eduardo M. R. A. Engel (1999) "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S, s) Approach," *Econometrica*, 67 (4), 783–826.

Caglio, Cecilia, Ronald M. Darst, and Şebnem Kalemli-Özcan (2022) "Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms," Working Paper.

Cao, Jin, Torje Hegna, Martin B. Holm, Ragnar Juelsrud, Tobias König, and Mikkel Riiser (2024) "The Investment Channel of Monetary Policy: Evidence from Norway," Working Paper.

Chang, Minsu, Xiaohong Chen, and Frank Schorfheide (2024) "Heterogeneity and Aggregate Fluctuations," *Journal of Political Economy, forthcoming.*

Chang, Minsu and Frank Schorfheide (2022) "On the Effects of Monetary Policy Shocks on Earnings and Consumption Heterogeneity."

Charalampakis, Emmanuel, Bastian Fagandini, Fabian Henkel, and Chiara Osbat (2022) "The Impact of the Recent Rise in Inflation on Lower-Income Households," *Economic Bulletin*.

Cimadomo, Jacopo, Domenico Giannone, Michele Lenza, Francesca Monti, and Andrej Sokol (2022) "Nowcasting with large Bayesian vector autoregressions," *Journal of Econometrics*, 231 (2), 500–519, 10.1016/j.jeconom.2021.04.

Cloyne, James, Clodomiro Ferreira, and Paolo Surico (2020) "Monetary Policy when Households have Debt: New Evidence on the Transmission Mechanism," *Review of Economic Studies*, 87 (1), 102–129.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia (2017) "Innocent Bystanders? Monetary policy and inequality," *Journal of Monetary Economics*, 88 (C), 70–89, 10.1016/j.jmoneco.2017.05.

Colciago, Andrea, Anna Samarina, and Jakob de Haan (2019) "Central Bank Policies And Income And Wealth Inequality: A Survey," *Journal of Economic Surveys*, 33 (4), 1199–1231, 10.1111/joes.12314.

Cooley, Thomas and Vincenzo Quadrini (2006) "Monetary policy and the financial decisions of firms," *Economic Theory*, 27 (1), 243–270.

Covas, Francisco and Wouter J. Den Haan (2012) "The Role of Debt and Equity Finance Over the Business Cycle," *The Economic Journal*, 122 (565), 1262–1286.

Curci, Nicola, Marco Savegnago, Giordano Zevi, and Roberta Zizza (2022) "The Redistributive Effects of Inflation: A Microsimulation Analysis for Italy," Occasional Papers 738, Banca d'Italia.

Del Negro, Marco, Michele Lenza, Giorgio Primiceri, and Andrea Tambalotti (2020) "What's up with the Phillips Curve?" *Brookings Papers on Economic Activity*, Spring.

Deng, Mengyu and Ming Fang (2022) "Debt Maturity Heterogeneity and Investment Responses to Monetary Policy," *European Economic Review*, 144, 1–23.

DiCecio, Riccardo and Michael T. Owyang (2010) "Identifying technology shocks in the frequency domain,"Technical report.

Doan, Thomas, Robert Litterman, and Christopher Sims (1984) "Forecasting and conditional projection using realistic prior distributions," *Econometric Reviews*, 3 (1), 1–100.

Drechsel, Thomas (2022) "Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations," Working Paper.

Ettmeier, Stephanie (2023) "No Taxation Without Reallocation: The Distributional Effects of Tax Changes," CRC TR 224 Discussion Paper Series crctr224$_2$023$_4$36, $UniversityofBonnandUniversityofMannheim$, G

Gertler, Mark and Simon Gilchrist (1994) "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109 (2), 309–340.

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri (2015) “Prior selection for vector autoregressions,” *The Review of Economics and Statistics*, 97 (2), 436–51.

Giannone, Domenico, Michele Lenza, and Lucrezia Reichlin (2019) “Money, Credit, Monetary Policy and the Business Cycle in the Euro Area: What Has Changed since the Crisis?”Technical Report 5, International Journal of Central Banking.

Gilchrist, S, J. W. Sim, and E. Zakrajšek (2014) “Uncertainty, financial frictions, and investment dynamics,” *Working Paper*.

Ivashina, Victoria, Luc Laeven, and Enrique Moral-Benito (2022) “Loan Types and the Bank Lending Channel,” *Journal of Monetary Economics*, 126, 171–187.

Jeenas, Priit (2019) “Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics,”Technical report.

Jungherr, Joachim, Matthias Meier, Timo Reinelt, and Immo Schott (2022) “Corporate Debt Maturity Matters For Monetary Policy.”

Kalemli-Ozcan, Sebnem, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas (2022) “How To Construct Nationally Representative Firm Level Data From The Orbis Global Database: New Facts And Aggregate Implications,” *NBER Working Paper*, 21558.

Khan, Aubhik and Julia K. Thomas (2008) “Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics,” *Econometrica*, 76 (2), 395–436.

Kobi, Yann and Christian Wolf (2020) “Aggregation in Heterogeneous-Firm Models: Theory and Measurement,” *MIT Working Paper*.

Krusell, Per, Kurt C. Thurwachter, and Jacob Weiss (2023) “Upwardly Mobile: The Response of Young vs. Old Firms to Monetary Policy,” Working Paper.

Lenza, Michele and Giorgio E. Primiceri (2022) “How to estimate a vector autoregression after March 2020,” *Journal of Applied Econometrics*, 37 (4), 688–699, 10.1002/jae.2895.

Lenza, Michele and Jiri Slacalek (2024) “How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area,” *Journal of Applied Econometrics,* *forthcoming.*

Litterman, Robert B (1979) "Techniques of forecasting using vector autoregressions," Technical report.

McKay, Alisdair and Christian K. Wolf (2023) "Monetary Policy and Inequality," *Journal of Economic Perspectives*, 37 (1), 121–44, 10.1257/jep.37.1.121.

Ottonello, Pablo and Thomas Winberry (2020) "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 88 (6), 2473–2502.

Pallotti, Filippo, Gonzalo Paz-Pardo, Jirka Slacalek, Oreste Tristani, and Gianluca Violante (2023) "Who bears the costs of inflation? Euro area households and the 2021–2022 shock," Technical report.

Uhlig, Harald (2005) "What are the effects of monetary policy on output? Results from an agnostic identification procedure," *Journal of Monetary Economics*, 52 (2), 381–419, https://ideas.repec.org/a/eee/moneco/v52y2005i2p381-419.html.

Recent Working Papers:

For a complete list of Working Papers published by Sveriges Riksbank, see www.riksbank.se

The Macroeconomic Effects of Trade Tariffs: Revisiting the Lerner Symmetry Result *by Jesper Lindé and Andrea Pescatori*	2019:363
Biased Forecasts to Affect Voting Decisions? The Brexit Case *by Davide Cipullo and André Reslow*	2019:364
The Interaction Between Fiscal and Monetary Policies: Evidence from Sweden *by Sebastian Ankargren and Hovick Shahnazarian*	2019:365
Designing a Simple Loss Function for Central Banks: Does a Dual Mandate Make Sense? *by Davide Debortoli, Jinill Kim and Jesper Lindé*	2019:366
Gains from Wage Flexibility and the Zero Lower Bound *by Roberto M. Billi and Jordi Galí*	2019:367
Fixed Wage Contracts and Monetary Non-Neutrality *by Maria Björklund, Mikael Carlsson and Oskar Nordström Skans*	2019:368
The Consequences of Uncertainty: Climate Sensitivity and Economic Sensitivity to the Climate *by John Hassler, Per Krusell and Conny Olovsson*	2019:369
Does Inflation Targeting Reduce the Dispersion of Price Setters' Inflation Expectations? *by Charlotte Paulie*	2019:370
Subsampling Sequential Monte Carlo for Static Bayesian Models *by David Gunawan, Khue-Dung Dang, Matias Quiroz, Robert Kohn and Minh-Ngoc Tran*	2019:371
Hamiltonian Monte Carlo with Energy Conserving Subsampling *by Khue-Dung Dang, Matias Quiroz, Robert Kohn, Minh-Ngoc Tran and Mattias Villani*	2019:372
Institutional Investors and Corporate Investment *by Cristina Cella*	2019:373
The Impact of Local Taxes and Public Services on Property Values *by Anna Grodecka and Isaiah Hull*	2019:374
Directed technical change as a response to natural-resource scarcity *by John Hassler, Per Krusell and Conny Olovsson*	2019:375
A Tale of Two Countries: Cash Demand in Canada and Sweden *by Walter Engert, Ben Fung and Björn Segendorf*	2019:376
Tax and spending shocks in the open economy: are the deficits twins? *by Mathias Klein and Ludger Linnemann*	2019:377
Mind the gap! Stylized dynamic facts and structural models *by Fabio Canova and Filippo Ferroni*	2019:378
Financial Buffers, Unemployment Duration and Replacement Labor Income *by Mats Levander*	2019:379
Inefficient Use of Competitors' Forecasts? *by André Reslow*	2019:380
How Much Information Do Monetary Policy Committees Disclose? Evidence from the FOMC's Minutes and Transcripts *by Mikael Apel, Marianna Blix Grimaldi and Isaiah Hull*	2019:381
Risk endogeneity at the lender/investor-of-last-resort *by Diego Caballero, André Lucas, Bernd Schwaab and Xin Zhang*	2019:382
Heterogeneity in Households' Expectations of Housing Prices – Evidence from Micro Data *by Erik Hjalmarsson and Pär Österholm*	2019:383
Big Broad Banks: How Does Cross-Selling A Affect Lending? *by Yingjie Qi*	2020:384
Unemployment Fluctuations and Nominal GDP Targeting *by Roberto Billi*	2020:385
FAQ: How do I extract the output gap? *by Fabio Canova*	2020:386

Drivers of consumer prices and exchange rates in small open economies *by Vesna Corbo and Paola Di Casola*	2020:387
TFP news, stock market booms and the business cycle: Revisiting the evidence with VEC models *by Paola Di Casola and Spyridon Sichlimiris*	2020:388
The costs of macroprudential deleveraging in a liquidity trap *by Jiaqian Chen, Daria Finocchiaro, Jesper Lindé and Karl Walentin*	2020:389
The Role of Money in Monetary Policy at the Lower Bound *by Roberto M. Billi, Ulf Söderström and Carl E. Walsh*	2020:390
MAJA: A two-region DSGE model for Sweden and its main trading partners *by Vesna Corbo and Ingvar Strid*	2020:391
The interaction between macroprudential and monetary policies: The cases of Norway and Sweden *by Jin Cao, Valeriya Dinger, Anna Grodecka-Messi, Ragnar Juelsrud and Xin Zhang*	2020:392
Withering Cash: Is Sweden ahead of the curve or just special? *by Hanna Armelius, Carl Andreas Claussen and André Reslow*	2020:393
Labor shortages and wage growth *by Erik Frohm*	2020:394
Macro Uncertainty and Unemployment Risk *by Joonseok Oh and Anna Rogantini Picco*	2020:395
Monetary Policy Surprises, Central Bank Information Shocks, and Economic Activity in a Small Open Economy *by Stefan Laséen*	2020:396
Econometric issues with Laubach and Williams' estimates of the natural rate of interest *by Daniel Buncic*	2020:397
Quantum Technology for Economists *by Isaiah Hull, Or Sattath, Eleni Diamanti and Göran Wendin*	2020:398
Modeling extreme events: time-varying extreme tail shape *by Bernd Schwaab, Xin Zhang and André Lucas*	2020:399
The Effects of Government Spending in the Eurozone *by Ricardo Duque Gabriel, Mathias Klein and Ana Sofia Pessoa*	2020:400
Narrative Fragmentation and the Business Cycle *by Christoph Bertsch, Isaiah Hull and Xin Zhang*	2021:401
The Liquidity of the Government Bond Market – What Impact Does Quantitative Easing Have? Evidence from Sweden *by Marianna Blix Grimaldi, Alberto Crosta and Dong Zhang*	2021:402
Five Facts about the Distributional Income Effects of Monetary Policy *by Niklas Amberg, Thomas Jansson, Mathias Klein and Anna Rogantini Picco*	2021:403
When domestic and foreign QE overlap: evidence from Sweden *by Paola Di Casola and Pär Stockhammar*	2021:404
Dynamic Macroeconomic Implications of Immigration *by Conny Olovsson, Karl Walentin, and Andreas Westermark*	2021:405
Revisiting the Properties of Money *by Isaiah Hull and Or Sattath*	2021:406
The cost of disinflation in a small open economy vis-à-vis a closed economy *by Oleksandr Faryna, Magnus Jonsson and Nadiia Shapovalenko*	2021:407
On the Performance of Cryptocurrency Funds *by Daniele Bianchi and Mykola Babiak*	2021:408
The low-carbon transition, climate commitments and firm credit risk *by Sante Carbone, Margherita Giuzio, Sujit Kapadia, Johannes Sebastian Krämer, Ken Nyholm and Katia Vozian*	2022:409
Seemingly Irresponsible but Welfare Improving Fiscal Policy at the Lower Bound *by Roberto M. Billi and Carl E. Walsh*	2022:410
Pension Reform and Wealth Inequality: Evidence from Denmark *by Torben M. Andersen, Joydeep Bhattacharya, Anna Grodecka-Messi and Katja Mann*	2022:411

Sveriges Riksbank
Visiting address: Brunkebergs torg 11
Mail address: se-103 37 Stockholm

Website: www.riksbank.se
Telephone: +46 8 787 00 00, Fax: +46 8 21 05 31
E-mail: registratorn@riksbank.se