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ORIGINAL ARTICLE

Shock Transmission in Granular Economies: Impact of Pass-Through Effects of Idiosyncratic Microshocks to the Aggregate

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Abstract

This paper studies the importance of shocks to the largest firms on the aggregate output. Using firm-level data on eight European countries (2006–2019), we find that shocks to the largest firms explain an important part of aggregate fluctuations. Our paper brings several novelties. Firstly, in addition to the aggregate level, we extend the analysis of the transmission of firm-level shocks to study the shocks at the sectoral level. Secondly, we provide a novel measurement for demand-side shocks within granularity. We show that idiosyncratic shocks affecting the largest 20 firms can explain almost half of the output volatility, which is consistent with Gabaix (2011). Moreover, demand-side shocks contribute a greater share to this volatility compared to supply-side shocks. Finally, we show that the smaller the sample of the largest firms, the larger the propagation effect of the shocks to GDP. This suggests that a few large firms drive a large part of the aggregate volatility, while volatility of other larger firms balances out on average.

Keywords: Business cycle, Supply-side shocks, Demand-side shocks, Aggregate fluctuations, Granular residual

JEL classification: E32, O47, C23, L25, F23

1 Introduction

Aggregate fluctuations have traditionally been attributed to factors such as monetary and fiscal policies, government spending, aggregate demand shifts, and technological changes (Magerman et al., 2016). These are key mechanisms in real business cycle and New Keynesian models (e.g., Christiano et al., 2005; Kydland & Prescott, 1982). However, macroeconomic shocks alone do not fully explain aggregate volatility (Cochrane, 1994). Several crises, including the global financial crisis as well as the COVID-19 pandemic, highlighted that firm-level shocks, not just large common shocks, can spread across the economy, leading to substantial aggregate movements (Magerman et al., 2016; Stumpner et al., 2022).

This paper's motivation is thus to analyse whether firm-level shocks are able to explain aggregate fluctuations by examining the importance of shocks to the largest firms on the aggregate output. Given the dominance of large firms in modern economies, idiosyncratic shocks affecting these firms can result in significant aggregate shocks. As an example, for our sample, during 2007 to 2019, the average proportion of total sales of the largest 20 and 50 firms relative to GDP across all countries stood at 12.5% and 17.9%, respectively. Hence, one can argue than large firms represent a substantial share of the macroeconomic activity, which means analysing their actions is valuable for gaining insights into the overall economy. Several studies highlight the impact of firm-specific shocks on aggregate fluctuations. Gabaix (2011) finds that idiosyncratic shocks to the top 100 U.S. firms explain up to a third of GDP fluctuations. Blank et al. (2009) find that positive shocks at large banks decrease the probability of distress of small banks.

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Freund and Pierola (2015) demonstrate that the top five firms contribute up to 30% of nonoil exports in 32 countries, indicating that a single firm can shape the entire comparative advantage of a country.

Moreover, this paper also intersects with the literature that focuses on the significance of sectoral shocks in driving aggregate fluctuations, a concept pioneered by Long and Plosser (1983). The central idea is that idiosyncratic shocks impacting a single sector can yield notable aggregate effects if that sector is deeply interconnected with others through input–output linkages (see Acemoglu et al., 2012; Horvath, 1998). Theoretically, Acemoglu et al. (2012), Acemoglu et al. (2017), and Jones (2011) show that the propagation of idiosyncratic shocks and distortions through input–output linkages can lead to implications for both macroeconomic volatility and economic growth. Empirically, Acemoglu et al. (2015) analyse the impact of large shocks affecting certain firms or industries by examining the input–output network. Also, Carvalho and Gabaix (2013) define fundamental volatility as the volatility that would emerge from an economy solely composed of idiosyncratic sectoral or firm-level shocks. They show that fundamental volatility is responsible for the fluctuations in macroeconomic volatility across the major world economies. As evidence continues to indicate that the production networks in developed market economies are often controlled by a handful of "superstar" firms (Bernard et al., 2019), there remains a lack of understanding of the differences in the granular effects across countries, sectors, as well as different types of shocks.

Also, our paper makes a distinction between supply and demand shocks. Supply shocks impact firms' production capacity, affecting prices, quantities of factor inputs, or production technology. Such shocks cause price levels and real output to move in opposite directions; for example, an adverse shock raises prices and lowers output (Blinder & Rudd, 2013). Temporary negative supply shocks reduce output and employment. Though severe, recessions caused by these shocks are partially an efficient response to decreased economic capacity for goods and services (Guerrieri et al., 2022). Thus, decreased firm sales indicate a supply-side shock. Conversely, Benguria and Taylor (2020) conceptualise a demand-side shock as a reduced borrowing limit for households, leading to reduced consumption, repayment of previous debts, and a consequent decline in overall demand for goods. This reduction in aggregate demand prompts firms to scale back production and subsequently decrease their demand for intermediate inputs. In other words, lower material costs signal a demand-side shock, as also highlighted by Damijan et al. (2018). Similarly, Carvalho et al. (2016) observe that a drop in demand for a specific product compels firms to curtail their input usage, implying that material costs fall in response to reduced demand. Contrarily, when demand increases—such as through rising foreign demand—firms expand their procurement of materials, thereby driving up material costs (Dhyne et al., 2022).

Our contributions are threefold. Firstly, as most of the literature on granularity (Blanco-Arroyo et al., 2018; Fornaro & Luomaranta, 2018; Gabaix, 2011; Konings et al., 2022; Miranda-Pinto & Shen, 2019) focuses only on one country, we contribute to the literature by examining granular aspects and cross-country differences in firm size distributions. These differences in firm size distributions lead to differences in granularity and significant disparities in how firm shocks affect aggregate fluctuations across countries. One can argue that countries exhibit varied firm size distributions (Poschke, 2018), and our sample reflects these differences. Our findings reveal that when GDP growth is weaker (Italy, Spain), shocks to the largest 20 firms affect GDP growth positively and more strongly. Conversely, in countries with stronger GDP growth (Poland, Hungary), shocks to the largest 20 firms affect GDP growth less strongly but adversely. Secondly, the majority of studies examine only a supply-side shock, as they use measures such as labour productivity, TFP, and sales, which depict a supply-side shock (Ebeke & Eklou, 2017). We find that the economy experiences varying effects depending on the type of shock affecting the largest firms. Keynesian theory suggests changes in aggregate demand significantly impact GDP, while classical economists argue changes in aggregate demand have no effect on output (Samuelson & Nordhaus, 2010, p. 593). We address a gap in the literature by introducing a novel measurement for demand-side shocks. Our results show that granular effects are present not only in supply-side shocks but also in demand-side shocks. Also, estimates from fixed-effects models indicate that demand-side shocks have larger effects than supply-side shocks, confirming the Keynesian view rather than the classical macroeconomic theory. Moreover, demand-side shocks play a more significant role in driving output volatility compared to supply-side shocks, as evidenced by their greater explanatory power. Thirdly, by extending our analysis to study firm-level shocks at the sectoral level, we also provide evidence on the differences between sectors in the extent of granularity as we focus on sector-level volatility. This sectoral analysis shows that the three most granular sectors are wholesale, retail, and repair of motor vehicles, manufacturing, and construction.

This paper is organised as follows. Section 2 provides a literature review, followed by a theoretical model and a calibration which displays that these granular effects matter when analysing macroeconomic fluctuations. Section 4 presents the empirical approach as well as data used in this paper. Section 5 presents the main empirical results as well as several robustness checks. Section 6 concludes.

2 Literature review

Traditional theory, specifically the diversification argument based on the law of large numbers, dismisses the possibility that substantial aggregate fluctuations arise from individual shocks to firms or specific sectors. As Lucas (1977) argued, these shocks average out and only exert negligible effects on the overall economy. Consequently, aggregate output stabilises very rapidly around its mean. In an economy comprising n sectors that are subject to independent shocks, the magnitude of aggregate fluctuations would be proportional to $1/\sqrt{n}$. Hence, at highly disaggregated levels, only negligible effects are noticeable. This argument dismisses the existence of linkages between firms and sectors, even though these connections serve as a propagation mechanism for idiosyncratic shocks throughout the economy. Interconnections among sectors can lead to a slower stabilisation of aggregate output around its mean compared to what is proposed by the diversification argument. This implies that sectoral shocks play a more substantial role in driving aggregate fluctuations; a concept referred to as granularity (Acemoglu et al., 2012). Gabaix (2011) argues that when the firm size distribution has a very fat tail, aggregate volatility decreases in line with $1/\ln N$. Many aggregate fluctuations can be traced back to the "grains" of economic activity, particularly to large firms; an idea known as the granular hypothesis. This hypothesis argues that idiosyncratic shocks to large firms can create nontrivial aggregate shocks impacting GDP and, via general equilibrium, all firms. An economy is deemed granular if shocks to the largest firms can induce aggregate fluctuations (di Giovanni & Levchenko, 2012). Firm size distribution in Gabaix (2011) serves a similar function to the intersectoral network in Acemoglu et al. (2012).

The granular approach is used in analyses that explain the fluctuations of several macroeconomic indicators. Various studies indicate that a few large firms have a disproportionate effect on GDP fluctuations. As an example, Gabaix (2011) examines U.S. data from 1951 to 2008 and finds that idiosyncratic shocks impacting the top 100 firms contributed to roughly one third of GDP fluctuations. Likewise, Ebeke and Eklou (2017) investigate idiosyncratic shocks among the 100 largest firms across eight European countries from 2000 to 2013, concluding that 40 percent of GDP variation could be attributed to idiosyncratic shocks affecting these firms. Similarly, comparable effects are also found for Spain (Blanco-Arroyo et al., 2018), Finland (Fornaro & Luomaranta, 2018), and Australia (Miranda-Pinto & Shen, 2019). On the other hand, Wagner and Weche (2020) conclude that the German economy is not a granular economy. They find that idiosyncratic shocks to the largest 100 firms did not seem to have a substantial impact on explaining aggregate volatility, thus contradicting a considerable portion of the empirical evidence supporting the granular hypothesis. Furthermore, studies also explore the granular hypothesis in terms of its influence on aggregate sales, in addition to its effects on GDP. These studies confirm that firm-level shocks impact aggregate sales in several countries, including France (di Giovanni et al., 2014), Sweden (Friberg & Sanctuary, 2016), and Chile (Grigoli et al., 2023). Other studies confirm that other measures, such as total factor productivity (TFP), exhibit indications of granularity, including in the U.S. (Baqaee & Farhi, 2019), Ireland (Papa, 2019), and Kazakhstan (Konings et al., 2022). Lastly, the granular hypothesis is also examined by analysing data from financial institutions. Amiti and Weinstein (2018) use Japanese data from 1990 to 2010 and find that idiosyncratic bank shocks explain 30 to 40 percent of aggregate loan and investment fluctuations.

The literature on granularity is also closely related to the literature on the role of firm heterogeneity in explaining aggregate fluctuations in outcomes such as unemployment and trade. For instance, Moscarini and Postel-Vinay (2012) examine the role of large and small employers in job creation across different business cycles. They identify a negative correlation between the net job creation rate of large employers and the level of aggregate unemployment. Moreover, di Giovanni and Levchenko (2012) examine a model with heterogeneous firms that are subjected to idiosyncratic firm-specific shocks, calibrated using data for the 50 largest economies globally. They discover that smaller countries are more prone to higher volatility arising from idiosyncratic shocks to large firms as they have fewer firms. Furthermore, macroeconomic volatility increases with trade opening as large firms gain even more importance. Consequently, trade can trigger a 15–20% increase in aggregate volatility in some small open economies. Relatedly, Wagner (2013) uses panel data for German manufacturing exporting firms during the 2008–2009 crisis. The author shows that idiosyncratic shocks to very large firms play an important role in shaping the export collapse as the top 10 firms in an industry accounted for around one third of export fluctuations.

Lastly, it is crucial to differentiate the pass-through effects between small and large firms. Amiti et al. (2014) find that large import-intensive exporters in Belgium have a 50% exchange rate pass-through, while small nonimporting firms have nearly complete pass-through. Amiti et al. (2019) also show that small firms exhibit no strategic complementarities and a complete pass-through of marginal cost shocks into their domestic prices, while large firms show strong strategic complementarities and an incomplete pass-through to their domestic prices.

3 Theoretical model and calibration

This section briefly presents the model proposed by Gabaix (2011) and provides a calibration of GDP volatility using Orbis data. Gabaix uses an islands economy with N firms. Production is assumed to be exogenous, and initially there are no linkages between firms. The main equation of the model depicts the below expression for standard deviation of GDP growth, denoted as σ_{GDP}:

$$\sigma_{\text{GDP}} = \left(\sum_{i=1}^{N} \sigma_i^2 \left(\frac{S_{it}}{Y_t} \right)^2 \right)^{\frac{1}{2}} \tag{1}$$

Here, total GDP is labelled as Y_t, σ_i represents firm i's volatility, and S_{it} is the quantity of a homogenous consumption good produced by firm i in time t without any factor input. Hence, the variance of GDP represents the weighted sum of the variance σ_i^2 of idiosyncratic shocks where weights are equal to the squared share of output produced by firm i (Gabaix, 2011).

Next, the examination of the $1/\sqrt{N}$ argument for the (ir)relevance of idiosyncratic shocks is presented. If one assumes there is a large number of firms, N, idiosyncratic fluctuations disappear in the aggregate. Also, assuming that firms have initially identical size that is equal to $1/N$ of GDP and identical standard deviation ($\sigma_i = \sigma$), the standard deviation of GDP growth, denoted as σ_{GDP}, is then equal to $\sigma_{\text{GDP}} = \frac{\sigma}{\sqrt{N}}$. According to Gabaix (2011), the estimate of firm volatility σ is equal to 12%, and an economy has $N = 10^6$ firms. The GDP volatility per year is then equal to 0.012%. Arguably, that is far too distant from the empirically measured size of macroeconomic fluctuations of approximately 1%, thus economists often resort to aggregate shocks. More general modelling assumptions anticipate a $1/\sqrt{N}$ scaling (Gabaix, 2011). The above proposition assumes that firm size distribution is thin-tailed. According to Axtell (2001), the size distribution of U.S. firms is instead well approximated by the power law; more specifically, it exhibits the Zipf distribution. This result applies globally, and there is an improving understanding of the origins behind this distribution. Accordingly, it has been shown that if the firm size distribution has fat tails, σ_{GDP} declines more slowly than $1/\sqrt{N}$. More specifically, if one knows the GDP of several countries, but not the size of their respective firms, except that, for example, they exhibit Zipf's law, the volatility of a country of size N is proportional to $1/\ln N$ (Gabaix, 2011).

We then follow Gabaix (2011) to account for input–output linkages and for the endogenous response in inputs to initial disturbances. Our calibration shows that the effects are of the right order of magnitude to account for macroeconomic fluctuations. First, assume an economy with N competitive firms that buy intermediary inputs from one another. Firm i exhibits Hicks-neutral productivity growth. It can be observed that TFP shocks can be calculated without knowing the input–output matrix, as the sufficient datum for the impact of firm i is its size, measured by its sales. Moreover, h is the sales Herfindahl index:

$$h = \left(\sum_{i=1}^{N} \left(\frac{\text{sales}_{it}}{\text{GDP}_t} \right)^2 \right)^{\frac{1}{2}} \tag{2}$$

Moreover, the volatility of the TFP growth, denoted as σ_{TFP}, is equal to $\sigma_{\text{TFP}} = h\sigma_\pi$, where σ_π is the standard deviation for growth rates of total sales and h is the sales Herfindahl index. One can then examine the empirical magnitude of the key variables of the volatility of the TFP growth, namely the volatility of firm size of the largest firms. As an example, the volatility of one of the measures of growth rates includes $\Delta \ln \text{sales}_{it}$. For each year one then calculates the cross-sectional variance among the largest firms of the previous year and takes the average. The volatility of GDP can be calculated as $\sigma_{\text{GDP}} = \mu\sigma_\pi h$, where μ reflects factor usage, σ_π is the standard deviation for growth rates of total sales, and h is the sales Herfindahl index. The following three benchmarks can be used for factor usage. Firstly, a short-term model with fixed capital in the short run and the Frisch elasticity of labour supply equal to 2 yields $\mu = 1.8$. Secondly, assuming flexible supply of capital, the value of μ amounts to 4.5. Lastly, under the neoclassical growth model where TFP is assumed to follow a geometrical random walk where only capital can be accumulated in the long run, μ is equal to 1.5. One can take the average of the three above values and obtain $\mu = 2.6$ (Gabaix, 2011).

Fig. 1 summarises the selected measures for our sample, with the sales Herfindahl index and GDP volatility displayed on the left y axis, and the standard deviation of sales growth rates for the 20 largest firms shown on the right y axis. Here, the average

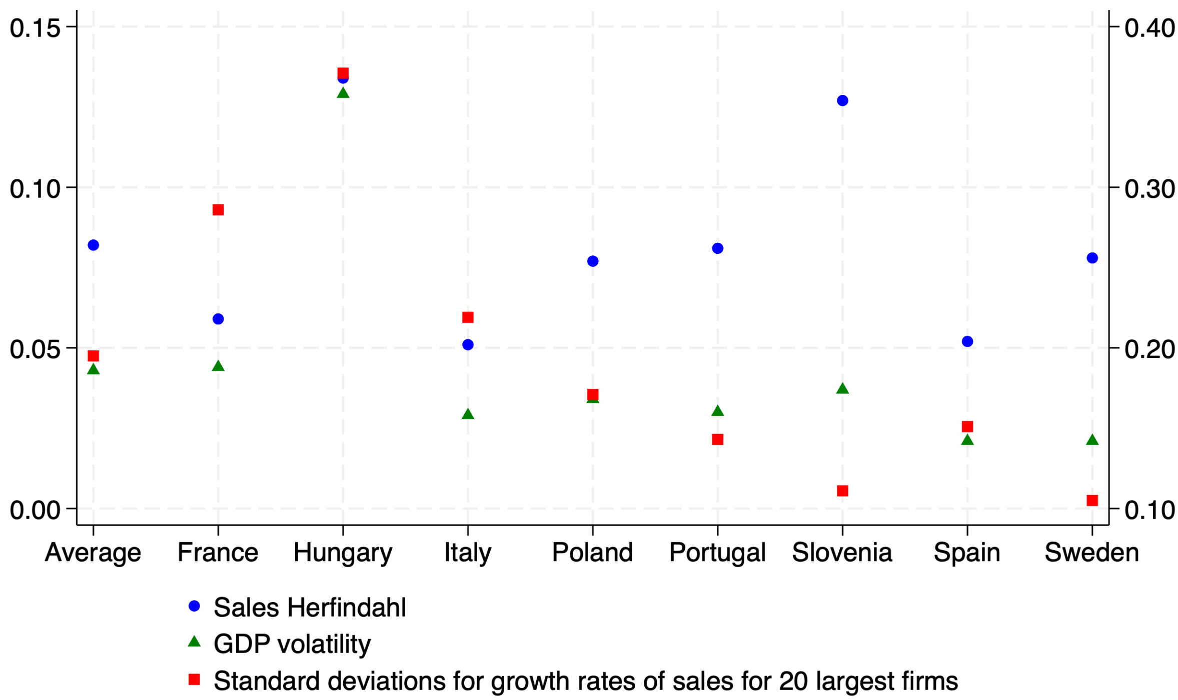

Fig. 1. Sales Herfindahl, standard deviations for growth rates of sales, and GDP volatility (in %), by country (average for 2006–2019). Source: Orbis database.

sales Herfindahl is quite large for the selected European countries during the period 2006–2019, as it amounts to around 8.2%. Hungary (13.4%) and Slovenia (12.7%) exhibited the highest values (the number of large firms is relatively large, compared to GDP), while Italy (5.1%), Spain (5.2%), France (5.9%), Poland (7.7%), Sweden (7.8%), and Portugal (8.1%) all had values below the average of the sample (the number of small firms is relatively large, compared to GDP). Next, in order to calculate GDP volatility, standard deviations for growth rates of sales for the 20 largest firms in each country were calculated. For each year t, the cross-sectional variance of growth rate was calculated, $\sigma_t^2 = K^{-1}\sum_{i=1}^{K} g_{it}^2 - \left(K^{-1}\sum_{i=1}^{K} g_{it}\right)^2$, with $K = 20$. The average standard deviation is $\left(T^{-1}\sum_{t=1}^{T}\sigma_t^2\right)^{1/2}$. On average, the standard deviation for growth rates of sales for all countries is around 19.5%. The largest firms were the most volatile in Hungary, France, and Italy. In contrast, the largest firms were less volatile in Sweden, Slovenia, Portugal, Spain, and Poland as these countries all had values below the sample average. Finally, the average GDP volatility for all countries in the sample stands at around 4.3%. Arguably, this suggests that idiosyncratic volatility is significant enough at the macrolevel.

For comparison, in Gabaix (2011) the standard deviation for growth rates of total sales is 12%. The sales Herfindahl index is quite low, amounting to 5.3%, whereas it accounts for 22% in an average over all countries. In other words, the U.S. is a country with relatively small firms compared to GDP. Thus, the granular hypothesis would likely be harder to prove. GDP volatility (σ_{GDP}) for the U.S. amounts to 1.7%, whereas for a typical country GDP volatility amounts to 6.8%. Arguably, this is on the order of magnitude of GDP fluctuations; thus, at the macrolevel idiosyncratic volatility appears to be quantitatively large enough to matter (Gabaix, 2011).

4 Empirical approach

We test whether granular effects are observed in propagation of shocks on the set of eight European countries. Firstly, we follow the methodology proposed by Gabaix (2011), while employing indicators for both supply- and demand-side shocks. The granular residual, serving as an indicator of these shocks, is derived as the weighted sum of large firms' sales or material costs growth rate subtracted from the corresponding average growth rate across firms. Specifically, changes in the sales growth rate reflect a supply-side shock, whereas changes in the growth rate of material costs signify a demand-side shock. Secondly, the paper extends the analysis by investigating the impact of shocks in the largest firms at the sectoral level. These shocks are defined as the annual differences in the shares of either sales (supply side) or material costs (demand side) of the largest firms in the sectoral value of both variables.

This section firstly outlines the econometric approach for both the aggregate granular residual and for sectoral level analysis. Secondly, descriptive statistics are presented. The baseline model tests whether GDP is affected by either supply- or demand-side shocks in the largest firms; shocks transmitting through the largest 20 firms in case of aggregate granular residual and the largest five firms for sectoral analysis. Robustness checks for the granular residual include additional estimations of the growth rates of sales and material costs (Eqs. (5) and (6) below). We also vary the definition of "large firms" to include 3, 5, 10, 20, 50, or 100 largest firms for the granular residual and 3, 5, and 10 largest firms for sectoral analysis.

4.1 Econometric approach

This section firstly presents a parsimonious measure—granular residual—of the shocks to the 20 largest firms, ranked by their lagged sales. The main challenge lies in identifying idiosyncratic shocks. Aggregate shocks may affect large firms, rather than shocks in the largest firms driving aggregate fluctuations. This "reflection problem" does not have a general solution (Manski, 1993). We use various tools to measure the share of idiosyncratic shocks. Moreover, granular residuals are constructed for each country separately. Focusing on the country average growths enables the removal of the influences stemming from the structural disparities in sectoral productivity growth across different countries (Ebeke & Eklou, 2017).

While we address potential simultaneity concerns via mean differencing and fixed effects, we acknowledge that this approach may not fully isolate causal effects. Ideally, an instrumental variable strategy or dynamic panel framework would strengthen identification. Here, we follow the approach of Gabaix (2011) and Ebeke and Eklou (2017), who also rely on OLS regressions and a fixed-effects model in similar granular residual setups.

Firstly, to account for supply-side shocks, one can use the change in sales growth rate of firm i in country c, at time t, denoted as g_{ict} (aligned with several studies that examine supply-side shock as sales growth, see, e.g., Guerrieri et al., 2022):

$$g_{ict} = \frac{\text{sales}_{i,t} - \text{sales}_{i,t-1}}{\text{sales}_{i,t-1}} \tag{3}$$

Creating the granular residual by using sales growth indicates that the source of aggregate fluctuations lies in supply-side shocks. Nonetheless, to account for demand-side shocks one can examine a change in the material costs growth rate of firm i in country c, at time t, denoted as z_{ict} (see Damijan et al., 2018):

$$z_{ict} = \frac{\text{MC}_{i,t} - \text{MC}_{i,t-1}}{\text{MC}_{i,t-1}} \tag{4}$$

Rather than relying solely on the previously defined expressions for changes, we estimate firm-level growth rates for the largest K firms to capture both sales and material cost dynamics more effectively. Specifically, we regress changes in sales and material cost growth rates on two specifications, summarised in X_{ict}: firstly, on the mean growth rates of the top K firms and their interaction with log sales (firm size), and secondly, on their interaction with the square of log sales as a robustness check, as shown below:

$$g_{ict} = \beta' X_{ict} + \varepsilon_{ict} \tag{5}$$

$$z_{ict} = \beta' X_{ict} + \varepsilon_{ict} \tag{6}$$

These regressions allow us to extract residuals following the methodology of Gabaix (2011), and these residuals serve as granular shocks representing the idiosyncratic component of firm-level growth. Ultimately, our objective is to assess whether this idiosyncratic component, captured in error term—denoted as ε_{ict}—can explain fluctuations in GDP growth. Next, the ideal granular residual, denoted as Γ^*_{ct}, can be empirically approximated by the equation of the growth in GDP:

$$\Gamma^*_{ct} := \sum_{i=1}^{K} \frac{S_{ic,t-1}}{S_{c,t-1}} \varepsilon_{ict} \tag{7}$$

The residual represents the sum of idiosyncratic firm shocks, weighted by firm relative size. Put differently, the weight is the ratio of the lagged sales of the firm ($S_{ic,t-1}$) over the total lagged sales ($S_{c,t-1}$), similarly as in Konings et al. (2022). Then, one needs to investigate what share of the total variance of GDP growth originates from the granular residual, as the theory states that GDP growth is $g_{Yt} = \mu\Gamma^*_t$. Importantly, ε_{ict} needs to be extracted by estimating the evolution of sales growth for the largest K firms of the previous year on a vector of observables specified above. The estimate of idiosyncratic firm-level supply-side shocks can be formed as $\widehat{\varepsilon_{ict}} = g_{ict} - \widehat{\beta'} X_{ict}$ or $\widehat{\varepsilon_{ict}} = z_{ict} - \widehat{\beta'} X_{ict}$ for demand-side shocks. The granular residual is thus defined as (Gabaix, 2011;

Konings et al., 2022):

$$\Gamma_{ct} := \sum_{i=1}^{K} \frac{S_{ic,t-1}}{S_{c,t-1}} \widehat{\varepsilon_{ict}} \tag{8}$$

If the measured granular residual Γ_{ct} is close to the ideal granular residual Γ^*_{ct}, identification is achieved. Gabaix (2011) then presents the particularisation that is transparent and does not demand much data, while turning out to do as well as the more complicated measures. The simplest procedure is to control for the mean growth rate in the sample. Put differently, $X_{ict} = \bar{g}_{ct}$ or $X_{ict} = \bar{z}_{ct}$, where $\bar{g}_{ct} = K^{-1} \sum_{i=1}^{K} g_{ict}$ and $\bar{z}_{ct} = K^{-1} \sum_{i=1}^{K} z_{ict}$. As indicated by the equations, we compute the average across the largest K firms. In our baseline analysis, K is set to 20, corresponding to the 20 largest firms, while we also vary K in robustness checks. Next, the granular residual is the weighted sum of a firm's growth rate difference from the average growth rate (Gabaix, 2011):

$$\Gamma^s_{ct} = \sum_{i=1}^{K} \frac{S_{ic,t-1}}{S_{c,t-1}} (g_{ict} - \bar{g}_{ct}) \tag{9}$$

$$\Gamma^d_{ct} = \sum_{i=1}^{K} \frac{S_{ic,t-1}}{S_{c,t-1}} (z_{ict} - \bar{z}_{ct}) \tag{10}$$

This adjustment helps to remove the impacts of common shocks affecting all firms and sectors in each country every year. These encompass, among other factors, policy shocks related to aggregate demand, such as fiscal and/or monetary policies, significant structural reforms (Ebeke & Eklou, 2017). Lastly, the largest 20 firms are sorted according to their year-over-year lagged sales. Utilising lagged sales ensures that even if large companies face a negative shock, they remain included in the sample of large firms (Gabaix, 2011; Konings et al., 2022).

Then, GDP growth (using pooled OLS estimation) is regressed on the measure of granularity (Γ^s_{ct} and Γ^d_{ct}, respectively) interacted with countries and on a crisis dummy, where ϑ_{ct} presents the error term:

$$\begin{aligned} Y_{ct} = \beta_1 + \beta_2 \Gamma^s_{ct} \ + \ \beta_3 \Gamma^s_{ct} * \text{Country}_t \\ + \beta_4 \text{Country}_t + \ \beta_5 \text{Crisis}_t + \vartheta_{ct} \end{aligned} \tag{11}$$

$$\begin{aligned} Y_{ct} = \beta_1 + \beta_2 \Gamma^d_{ct} \ + \ \beta_3 \Gamma^d_{ct} * \text{Country}_t + \beta_4 \text{Country}_t \\ + \beta_5 \text{Crisis}_t + \vartheta_{ct} \end{aligned} \tag{12}$$

More specifically, the model tests whether the measure of granularity (also interacted with country fixed effects) is able to explain GDP growth. The global financial crisis (GFC) dummy accounts for the global financial crisis and includes the period from 2009 to 2012. We explore two types of shocks. To ensure the robustness of our analysis, we preform various tests by varying the definition of "largest" firms when computing the granular residual. Moreover, another robustness check involves expanding the set of explanatory variables in estimating both sales and material costs growth rates as alongside g_{ict} and z_{ict} and their interactions with the logarithm of firm size, their interactions with the square of the logarithm of firm size are also included. Additionally, we use a fixed-effects model to estimate the average impact of both supply and demand shocks to GDP growth.

Next, the paper extends the analysis by investigating demand and supply shocks within the samples of largest firms at the sectoral level. Supply and demand shocks are defined as the annual differences in the shares of sales or material costs of the largest firms in the sectoral value of the corresponding variable, respectively.[1] Here, we acknowledge that sectoral dynamics may be more comprehensively captured through the use of dynamic panel models. In this study, we partially address these dynamics by including country fixed effects and estimating separate regressions for each sector, thereby accounting for sector-specific trends and unobserved heterogeneity. While this approach helps mitigate concerns related to omitted dynamics, we recognise that future research could benefit from employing dynamic panel estimators to capture cumulative and lagged effects across sectors more explicitly.

The supply-side shock is defined as:

$$\tau^s_{ct} = \frac{1}{K} \sum_{i=1}^{K} \left[\frac{\text{sales}_{i,t}}{\text{sales}_{j,t}} - \frac{\text{sales}_{i,t-1}}{\text{sales}_{j,t-1}} \right] \tag{13}$$

Similarly, the demand-side shock is defined as:

$$\tau^d_{ct} = \frac{1}{K} \sum_{i=1}^{K} \left[\frac{\text{MC}_{i,t}}{\text{MC}_{j,t}} - \frac{\text{MC}_{i,t-1}}{\text{MC}_{j,t-1}} \right] \tag{14}$$

Here, i depicts the firm, j indicates the sector, and t is the year. The paper identifies the $K = 5$ largest firms in each sector in the Orbis dataset, using the previous year's sales and, as before, excluding firms in the oil, energy, and finance sectors. GDP growth is then regressed on this novel measure of granularity with country interactions terms and the GFC dummy for each sector individually.

$$\begin{aligned} Y_{ct} = \beta_1 + \beta_2 \tau^s_{ct} \ + \ \beta_3 \tau^s_{ct} * \text{Country}_t + \beta_4 \text{Country}_t \\ + \beta_5 \text{Crisis}_t + \vartheta_{ct} \end{aligned} \tag{15}$$

[1] Note that the values are not deflated.

$$Y_{ct} = \beta_1 + \beta_2\tau^d_{ct} + \beta_3\tau^d_{ct} * \text{Country}_t + \beta_4\text{Country}_t + \beta_5\text{Crisis}_t + \vartheta_{ct} \quad (16)$$

The model investigates the impact of two types of shocks on GDP at the sectoral level. Firstly, the model examines a supply-side shock in the largest five firms, where the granular residual (τ^s_{ct}) is the difference in the shares of sales of the largest firms in the sectoral sales. Secondly, the model investigates a demand-side shock in the largest five firms, where the granular residual (τ^d_{ct}) is the difference in the shares of material costs of the largest firms in the sectoral material costs. The crisis dummy represents the same period as in the previous model. To ensure the robustness of our analysis, we explore different definitions of "largest firms" in specifying measures of granularity.

4.2 Data

We use firm-level data from the Orbis database (Bureau van Dijk) by KU Leuven. The Orbis database includes information on both listed and unlisted firms. The financial and balance sheet data originate from national business registries, which adhere to country-specific legal and administrative filing mandates. While most countries require that limited liability firms register upon formation, the criteria in terms of the firm size for reporting balance sheet details vary among countries (Kalemli-Ozcan et al., 2022).[2] With millions of firms, Orbis is a valuable research resource. The data include annual observations from 2006 to 2019 of the following variables: firm ID, sales, and material costs. Following Bajgar et al. (2020) we rely on unconsolidated accounts to avoid duplicating accounts. Additionally, many large firms do not report consolidated accounts, and the majority of firms in Orbis provide only unconsolidated accounts. Consequently, we base our analysis on unconsolidated data.[3] While Orbis tends to be biased towards larger firms, this bias varies across sectors. By including all sectors (except finance and mining) we aim to mitigate this bias to some extent. To address Orbis limitations, we focus on eight European countries selected based on specific criteria. According to Bajgar et al. (2020), these countries demonstrate relatively high coverage of aggregate employment, output, and value added, do not have rounding issues, have a low prevalence of limited financial (LF) accounts, and feature a high percentage of firms that file accounts that are then reported to Orbis (Kalemli-Ozcan et al., 2022). Therefore, we believe that for these selected eight countries the analysis is robust. Next, we adopt a balanced sample approach, requiring firms included in the sample to be present throughout the entire period.[4] Additionally, missing, negative, or zero values for sales or material costs are replaced with linear interpolations. If after linear interpolation, there is still at least one missing value for either sales or material costs for a certain firm, that firm is excluded. Moreover, when the growth rate of sales or material costs surpasses 20% (the same threshold as Gabaix, 2011), these values are replaced with interpolated values.[5] Industries are categorised using 2-digit NACE (Nomenclature of Economic Activities) Rev. 2 codes.

Like other studies on granularity, we exclude firms engaged in mining (due to fluctuations of worldwide commodity prices) and financial institutions (as sales are a poor proxy for their output). Excluding these firms has minimal impact, while it is conceptually more appropriate. The ten sectors covered are agriculture, forestry and fishing; manufacturing; water supply, sewerage, waste management; construction; wholesale, retail, and repair of motor vehicles; transportation and storage; accommodation and food services; information and communication; real estate; and scientific technical and other business activities. Lastly, data for GDP growth rates are obtained from the IMF World Economic Outlook Database.

Table 1 provides data on average sales, material costs, as well as number of firms in the sample during the 2006–2019 period. For the largest 20 firms across analysed countries, the rankings are based on lagged sales, mirroring the approach used in the empirical analysis. The full data consist of approximately 5.6 million firms on an annual basis. One can see that there are notable differences in sales and material costs between average firms and the largest firms. Descriptive data for the largest 50 firms can be found in the appendix (Table A1).

Table 2 shows the skewness and kurtosis when all firms in the sample are plotted according to their size (based on log sales) in year 2019 (the last year in the sample).[6] Results indicate that skewness for selected countries lies around −0.076, varying from −0.392 for Italy to 0.14 for Slovenia, indicating the distributions are slightly skewed. All countries

[2] For detailed information on which firms are excluded in particular countries, please refer to Kalemli-Ozcan et al. (2022), Table A.6.1.
[3] Should duplicate accounts with the same ID still exist and one of them has the consolidation code U2, the other accounts are removed.
[4] As some firms do not report their financials every year, excluding them only due to inavaliblity of data can disort the results.
[5] Several studies using Orbis data apply interpolation and imputation to improve data quality (Fujimoto et al., 2022; Gal, 2013; Kalemli-Ozcan et al., 2022). These approaches help ensure more reliable firm-level analysis from Orbis data and make the results more robust. For possible biases please refer to Kalemli-Ozcan et al. (2022).
[6] A normal distribution is characterised by a skewness of 0 and a kurtosis of 3.

Table 1. Descriptive statistics for all and for largest 20 firms, by country.

	All firms			Largest 20 firms	
	Sales (in million EUR)	Material costs (in million EUR)	No. of firms	Sales (in million EUR)	Material costs (in million EUR)
All countries	3.183	2.398	5,579,619	3845	2360
Spain	2.664	1.868	764,040	6427	4457
	(69.906)	(59.191)		(3653)	(2964)
France	3.575	2.650	788,813	13,212	7927
	(132.933)	(113.248)		(12,913)	(10,651)
Hungary	0.950	6.929	353,316	758	510
	(29.837)	(74.298)		(546)	(513)
Italy	2.762	1.959	1,637,572	5159	3019
	(86.567)	(71.363)		(4953)	(3819)
Poland	11.006	3.154	1,097,413	2441	1198
	(430.934)	(43.874)		(3568)	(1444)
Portugal	1.133	0.874	279,831	1184	709
	(26.984)	(26.141)		(866)	(812)
Sweden	2.476	1.195	565,874	1072	713
	(59.057)	(17.067)		(579)	(506)
Slovenia	0.900	0.558	92,761	503	343
	(17.286)	(14.822)		(355)	(302)

Note. Mean values (standard deviation).
Source: Orbis database.

Table 2. Skewness and kurtosis based on log sales for 2019, by country.

	Skewness	Kurtosis	p value for Shapiro–Wilk test	p value for Shapiro–Francia test
Spain	−0.058	4.42	.00000	.00001
France	0.113	3.70	.00000	.00001
Hungary	−0.166	3.78	.00000	.00001
Italy	−0.392	5.47	.00000	.00001
Poland	−0.140	2.90	.00000	.00001
Portugal	0.008	4.40	.00000	.00001
Sweden	−0.113	3.88	.00000	.00001
Slovenia	0.140	4.23	.00000	.00001

Source: Orbis database.

(except Poland) exhibit excess kurtosis (> 3), indicating a nonnormal, leptokurtic, distribution. Leptokurtic distributions are characterised by a higher peak, thinner "shoulders," and fatter tails. This can also be seen from Fig. A1 in the appendix, which shows firm size distributions (based on log sales) for year 2019 for each country. The presence of these fat tails, as can be seen from our data, causes the central limit theorem to break down, allowing idiosyncratic shocks to large firms to influence aggregate outcomes. In turn, this implies that aggregate outcomes can be disproportionately driven by a few large, idiosyncratic shocks, including those to large firms, sectors, or business groups, which do not necessarily average out at the macrolevel (Gabaix, 2011). Moreover, to mitigate heteroskedasticity, we applied two standard corrections. First, we used robust standard errors clustered at country level to ensure valid inference. Second, we log-transformed firm size to reduce skewness and stabilise variance, minimising the influence of large firms and improving model fit.

Next, the largest firms are segmented into ten distinct sectors based on their area of activity, as indicated by their respective NACE codes. These largest 20 firms predominantly operate in manufacturing and wholesale, retail, and repair of motor vehicles as these firms comprise just over 74% of all firms across all countries. The figure of each country's sectoral decomposition over the examined period is provided in the appendix (Fig. A2). This figure displays the distribution of the 20 largest firms by sector in each country over time and illustrates how the dominant industries among leading firms have shifted over time, reflecting broader economic and structural changes within each country. Lastly, Fig. A3 (in the appendix) shows GDP growth alongside two measures of granular residuals—the traditional supply-side version based on Gabaix (2011) and our novel demand-side measure—across our eight European countries from 2007 to 2019. The residuals are calculated using data from the largest 20 firms in each country. In our selected sample, most prominently in Spain, France, Italy, Poland, and Sweden, both residuals track GDP growth closely, with visible comovement during downturns and recoveries. Overall, the figure supports the idea that firm-level shocks can play a meaningful role in macroeconomic dynamics, and that both shock measures may be relevant in explaining some country-specific business cycle patterns.

5 Empirical results

This section presents econometric results derived from estimating the granular residual models (11) and (12) at the aggregate and sectoral levels, fixed-effects model, as well as robustness checks. Firstly, to calculate the granular residual, we identify the 20 largest firms by country and year based on the previous year's sales. To handle outliers in the database, we follow Gabaix (2011) and winsorise the extreme demeaned growth rates at 20%.[7] Secondly, the analysis is extended by investigating shocks within the largest firms at the sectoral level.

5.1 Granular residual

This section presents results derived from estimating the granular residual model (fixed-effects model and Eqs. (11) and (12)). We test whether GDP is affected by shocks in the largest 20 firms. Table 3 presents estimates of the effects of the granular residual on GDP growth (coefficients of granular residual from the fixed-effects model, coefficient β_3 for interactions and coefficient β_4 for country dummies in Eqs. (11) and (12)). These regressions support the granular hypothesis. The model's explanatory power is reasonably high, at 45.6% for supply-side shocks and 48.4% for demand-side shocks. Importantly, demand-side shocks play a more prominent role in driving output volatility as compared to supply-side shocks.

As shown by the estimates of the fixed-effects model, the impact of the average demand-side shock across all countries is significant as well as larger than that of the supply-side shock. Next, pooled OLS regression indicates that Spain (our controlling country) exhibits positive coefficients, suggesting that shocks in the largest firms have procyclical effects on GDP growth. Relative to Spanish granular effects France, Italy, Sweden, and Slovenia also show procyclical effects on GDP growth. Conversely, for Portugal we find negative coefficients, indicating countercyclical effects of the largest firms on GDP growth. This might be due to severe effects encountered during the GFC or due to a specific sectoral structure of large firms (composition effect). Supply-side shocks in the largest 20 firms have countercyclical effects in Hungary and Poland, while the opposite holds for demand-side shocks.

During the observed period, 2007–2019, the average GDP growth rates were lower in Italy, Portugal, Spain, and France, as compared to Poland, Sweden, Hungary, and Slovenia. Granular effects of countries with lower average GDP growth rates (Italy, Portugal, Spain) are the strongest, while granular effects of countries with higher average GDP growth rates (Poland, Hungary, and Sweden) are the weakest. Fig. 1 shows the relative importance of large firms (sales Herfindahl) as well as volatility of large firms. For Italy, Spain, and France (countries with a more equal size distribution), empirical evidence suggests that granular effects are even stronger compared to other countries. On the other hand, even though Hungary and Slovenia are countries where, relative to GDP, large firms tend to be more dominant, the granular effects are relatively weak compared to other countries. This could reflect institutional or structural differences beyond the scope of this paper's analysis.

5.2 Firm-level shocks at the sectoral level

This section provides results obtained from sectoral analysis by estimating models (15) and (16). Note that here we test whether GDP is affected by shocks in the largest five firms (instead of 20 firms) at the sectoral level. The full results are reported in Tables A2 and A3 in the appendix. Here, we first describe all results and then proceed with sectors where the strongest granular effects are observed. These regressions mostly support the granular hypothesis.

Firstly, the extent of granularity differs across countries, with Spain continuing to be the controlling country. The largest granular effects (the highest average coefficients for both shocks relative to Spanish effects) are observed in Italy and Sweden, and the weakest in Poland and France. The extent of granularity also differs across sectors; the largest granular effects are observed in wholesale, retail, and repair of motor vehicles, followed by manufacturing and construction. On the other hand, the weakest effects are estimated in real estate; water supply, sewerage, waste management; and scientific technical and other business activities. Cross-sectoral heterogeneity arises from differences in market concentration, interfirm

[7] When estimating $\widehat{\varepsilon_{ict}}$, we winsorised $\widehat{\varepsilon_{ict}}$ at $M = 20\%$. That is, by replacing it with $T(\widehat{\varepsilon_{ict}})$, if $T(x) = x$ if $|x| \leq M$ and $T(x) = \text{sign}(x)M$ if $|x| > M$. We also performed the regression without data winsorisation. Overall, the results are similar in significance, magnitude, and direction. Nonetheless, the winsorised data approach provides greater explanatory power.

Table 3. Coefficients of the granular residual for 20 largest firms, by country.

		Supply-side shocks in largest 20 firms	Demand-side shocks in largest 20 firms
		FE model	
Granular residual		0.603	0.926**
		(0.780)	(0.356)
Pooled OLS model			
Interactions	Spain	7.406***	7.336***
		(0.760)	(0.424)
	France	−6.211***	−6.840***
		(0.536)	(0.412)
	Hungary	−7.920***	−6.081***
		(0.944)	(0.427)
	Italy	−4.083***	−7.016***
		(0.112)	(0.254)
	Poland	−7.873***	−7.246***
		(0.669)	(0.450)
	Portugal	−10.047***	−8.279***
		(1.146)	(0.796)
	Sweden	−7.169***	−6.679***
		(0.535)	(0.409)
	Slovenia	−6.871***	−5.588***
		(0.008)	(0.171)
Country dummies	France	0.118***	0.592***
		(0.025)	(0.017)
	Hungary	1.069***	1.350***
		(0.040)	(0.012)
	Italy	−0.829***	−0.774***
		(0.035)	(0.026)
	Poland	3.285***	3.289***
		(0.014)	(0.014)
	Portugal	−0.116***	−0.127**
		(0.011)	(0.038)
	Sweden	1.118***	1.304***
		(0.043)	(0.015)
	Slovenia	1.035***	0.929***
		(0.124)	(0.009)
Global finanical crisis dummy		−2.380**	−2.480***
		(0.779)	(0.572)
Constant		1.505***	1.408***
		(0.249)	(0.189)
Observations		104	104
R^2		.456	.484

Note. Dependent variable: GDP growth. FE model, pooled OLS estimations. Reported coefficients for interactions are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France. Standard errors in the parentheses.
*** $p < .01$. ** $p < .05$. * $p < .1$.

linkages, and sector-specific dynamics. Highly concentrated and interconnected sectors (manufacturing and motor vehicle trade) are more exposed to firm-level shocks (di Giovanni et al., 2014; Eurostat, 2021; Gabaix, 2011). Di Giovanni et al. (2014) show that input–output linkages amplify shock transmission within sectors. The construction sector's sensitivity stems from its cyclical nature, driven by interest rates, housing demand, and public investment (van Sante, 2023). Shocks to large construction firms can be particularly impactful, with employment over twice as volatile as the cyclical component of GDP (Sun et al., 2013).

Next, the nature of different shock types can be examined. Across all countries, just above 60% of all coefficients have positive values, indicating shocks at the largest firms have a procyclical effect on GDP growth, which is mostly true for manufacturing, while the accommodation and food services sector exhibits countercyclical effects on GDP growth. Shocks at the largest firms in Portugal mostly have countercyclical effects on GDP growth across all sectors,

Table 4. Supply- and demand-side shocks in the largest five firms at the sectoral level for selected sectors, by country.

	Supply-side shock			Demand-side shock		
	Manufacturing	Construction	Motor vehicles	Manufacturing	Construction	Motor vehicles
ES	0.416**	−0.752***	0.352	0.675***	−0.143**	1.358***
	(0.134)	(0.143)	(0.594)	(0.093)	(0.058)	(0.314)
FR	−0.034	0.112	0.354	−0.274***	0.258	−0.778**
	(0.066)	(0.084)	(0.517)	(0.050)	(0.176)	(0.241)
HU	−0.813***	0.762***	−1.296**	−0.949***	0.353***	−1.787***
	(0.221)	(0.110)	(0.520)	(0.165)	(0.049)	(0.262)
IT	0.293***	0.465***	6.318***	0.036	0.048	4.814***
	(0.051)	(0.016)	(0.861)	(0.061)	(0.132)	(0.453)
PL	0.640***	1.053***	−0.743*	−0.330**	0.241*	−2.033***
	(0.089)	(0.087)	(0.353)	(0.101)	(0.124)	(0.168)
PT	0.759***	0.668***	−1.332***	0.037	−0.543***	−2.410***
	(0.095)	(0.021)	(0.264)	(0.049)	(0.051)	(0.130)
SE	2.629***	3.607***	1.406**	0.368***	3.278***	0.631*
	(0.504)	(0.207)	(0.593)	(0.104)	(0.176)	(0.293)
SI	0.286***	1.113***	−2.364***	−0.150***	0.577***	−2.976***
	(0.062)	(0.185)	(0.440)	(0.037)	(0.072)	(0.190)
GFC	−2.392***	−2.772***	−2.193**	−2.313***	−2.809***	−2.310***
	(0.615)	(0.742)	(0.639)	(0.622)	(0.677)	(0.617)
Const.	1.321***	0.973**	1.381***	1.321***	1.442***	1.532***
	(0.241)	(0.359)	(0.238)	(0.219)	(0.173)	(0.235)
Obs.	96	96	96	96	96	96
R^2	.471	.473	.531	.473	.496	.545

Note. Dependent variable: GDP growth. Pooled OLS estimations. Standard errors in the parentheses. GFC = global financial crisis dummy. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France.
*** $p < .01$. ** $p < .05$. * $p < .1$.

while the opposite holds for Sweden, which is consistent with the findings on the granular residual, presented in Section 5.1.

Secondly, based on the results of this analysis, the strongest significant granular effects are observed in the following three sectors: wholesale, retail, and repair of motor vehicles; manufacturing; and construction (Table 4). Therefore, these sectors are analysed further, although other sectors also exhibit significant, yet less strong values.

Results show that PIGS (Portugal, Italy, Spain) countries are most adversely affected by shocks in the largest five construction firms. Hungary, Poland, and Slovenia (as well as Portugal) are most adversely affected by shocks in the largest five firms in wholesale, retail, and repair of motor vehicles, while GDP growth in Hungary is also affected by shocks in large manufacturing firms. In France, supply-side shocks in the largest firms do not show significant effects on GDP growth, while demand-side shocks show procyclical effects in manufacturing and wholesale, retail, and repair of motor vehicles. In Sweden, all granular effects exhibit procyclical effects.

Based on these results, we can divide these eight countries into three groups. The first group consists of France and Sweden; the second group includes Portugal, Italy, and Spain (PIGS countries), and the third group is comprised of Poland, Slovenia, and Hungary. Looking at the data, in manufacturing, the granular effects are negative only in Hungary. These negative granular effects are, for example, observed in 2009, when Hungarian GDP fell by 6.6%, whereas the share of the largest five firms in sectoral sales and material costs increased by 3.9% and 3.8%, respectively. Even though GDP decreased, the largest firms still performed well. This indicates that the largest manufacturing firms have on average a countercyclical effect on GDP growth. However, the latter was more affected by sluggish performance of other parts of the economy. In construction, the granular effects are negative mostly in Spain, Italy, and Portugal. In Spain, these negative granular effects are observed especially in 2015, where Spanish GDP increased by 3.8%, whereas the share of the largest five firms in sectoral sales and material costs decreased by 2.8% and 2.2%, respectively. This indicates that even though GDP growth already started to accelerate, negative shocks in the largest construction firms still dragged down the rate of GDP growth. In Portugal, these negative granular effects are observed especially in 2016, when Portuguese GDP increased by 2%, whereas the share of the largest five firms in sectoral sales and material costs decreased by 2.9% and 2.2%, respectively. In Italy, these

Table 5. Coefficients of supply-side granular residuals for 3, 5, 10, 20, 50, and 100 largest firms, by country.

	Largest 3 firms	Largest 5 firms	Largest 10 firms	Largest 20 firms	Largest 50 firms	Largest 100 firms
Spain	−1.750*	−2.278*	2.725*	7.406*	5.735*	1.000*
France	9.053*	5.220*	−0.091	−6.211*	−4.348*	−0.235
Hungary	1.746*	2.414*	−4.005*	−7.920*	−6.880*	−1.594*
Italy	9.608*	5.620*	0.033	−4.083*	−2.929*	−5.241*
Poland	0.457	−1.004*	−3.444*	−7.873*	−6.447*	−1.667*
Portugal	−7.579*	−1.862	−6.202*	−10.047*	−6.194*	−1.700*
Sweden	29.679*	4.996	−9.211*	−7.169*	−6.922*	−3.314*
Slovenia	−1.171*	3.093*	2.545*	−6.871*	−7.902*	−5.550*
Observations	104	104	104	104	104	104
R^2	.473	.455	.491	.456	.471	.513

Note. Dependent variable: GDP growth. Pooled OLS estimations. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France.
* $p < .05$.

Table 6. Coefficients of demand-side granular residuals for 3, 5, 10, 20, 50, and 100 largest firms, by country.

	Largest 3 firms	Largest 5 firms	Largest 10 firms	Largest 20 firms	Largest 50 firms	Largest 100 firms
Spain	6.513	2.135	4.691*	7.336*	2.477*	1.050*
France	−2.949	1.08	−4.133*	−6.840*	−1.143*	−0.901*
Hungary	−5.714	−1.514	−5.028*	−6.081*	−1.325*	−0.457*
Italy	0.571	−1.664*	−4.733*	−7.016*	−2.641*	−1.289*
Poland	−6.336	−3.969*	−4.826*	−7.246*	−3.142*	−1.655*
Portugal	−7.403	−2.124	−5.788*	−8.279*	−2.750*	−1.364*
Sweden	20.606*	−9.083*	−6.731*	−6.679*	−1.885*	−0.933*
Slovenia	−5.991	−0.207	0.361*	−5.588*	−3.205*	−1.971*
Observations	104	104	104	104	104	104
R^2	.451	.434	.480	.484	.508	.513

Note. Dependent variable: GDP growth. Pooled OLS estimations. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France.
* $p < .05$.

negative granular effects are most prominent in 2013, when GDP fell by 3%. Nevertheless, the share of the largest five firms increased by 3.2%. In wholesale, retail, and repair of motor vehicles, the granular effects are negative in Hungary, Poland, Portugal, and Slovenia.

5.3 Robustness checks

Additional tests for the robustness of granular residual analysis involve further estimations of sales and material cost growth rates, considering their interactions with firm size and its squared value. Also, sample sizes vary, encompassing the largest 3, 5, 10, 20, 50, and 100 firms for the granular residual, and the largest 3, 5, and 10 firms for sectoral analysis.

Firstly, robustness checks are performed for the granular residual. For instance, when estimating the growth rates of sales and material costs (denoted as g_{it} and z_{it}, respectively) the model incorporates not only g_{ict} and z_{ict} and their interaction with firm size but also their interaction with firm size and its squared value. These estimations produce consistent results. Moreover, using a larger sample of top firms with $K = 50$ and $K = 100$ of firms provides similar results as well. These results strongly support the granular hypothesis. On the other hand, using a smaller sample of top firms, $K = 3$, $K = 5$, or $K = 10$, yields lower explanatory powers yet comparable results. Also note that one needs to be cautious in interpreting results from highly selective firm samples, for example, $K \leq 5$, as in these cases country coefficients exhibit somewhat lower levels of significance, especially for demand-side shocks. Tables 5 and 6 present these results. On average, countries exhibit stronger granular effects (higher coefficients) when a smaller sample of top firms is included. This indicates that a few largest firms affect GDP the most. Accordingly, as the sample size of the largest firms decreases, the impact of shocks on GDP increases, meaning that the volatility of a few of the largest firms significantly contributes to aggregate volatility, whereas the fluctuation of other large firms balances out on average. Nonetheless, there is a drop in the number of statistically significant coefficients when analysing the effect of 3 and 5 firms (especially for demand-side shocks). This implies that it might be suitable to analyse at least the 10 largest firms in an economy.

Secondly, defining largest firms by sector with $K = 3$ and $K = 10$ of firms produces consistent results (see Tables A4 and A5 in the appendix). Similar as before, we analyse the following three sectors: wholesale, retail, and repair of motor vehicles, manufacturing, and construction. On average, countries exhibit the strongest granular effects (the highest coefficients) when the 3 largest firms are analysed. This indicates that the largest three firms affect GDP the most. For both shock types, these largest firms have mostly procyclical effects on GDP growth. These results are aligned with the findings on the granular residual.

6 Conclusion

This paper demonstrates that idiosyncratic shocks to large firms can generate significant aggregate volatility, consistent with the breakdown of the central limit theorem in the presence of a fat-tailed firm size distribution. Using theory, calibration, and empirical evidence, we show that individual shocks affecting large firms are a key driver of business-cycle fluctuations as they explain a significant portion of aggregate volatility.

Our analysis makes several contributions. First, we highlight cross-country differences in firm size distributions, extending the largely single-country focus of existing literature. Second, we introduce a novel measure of demand-side shocks—complementing the literature's focus on supply-side shocks—and find that demand shocks have stronger effects on output volatility. Third, we examine sectoral-level granularity and show that sectors such as manufacturing, construction, and wholesale—where large firms are dominant and interlinked—exhibit the most pronounced granular effects. Finally, robustness tests confirm that the smaller the subset of top firms considered, the greater their shock propagation to GDP. We conclude that shocks to the largest 20 firms account for nearly half of aggregate output volatility and additionally, we show that demand-side shocks account for a larger portion of output volatility than supply-side shocks.

These findings have important implications for both macroeconomic modeling and policy. Traditional models that rely on representative agents or homogenous sectors may underestimate the impact of firm-specific dynamics. Incorporating granular residuals into forecasting models could improve their ability to predict fluctuations. From a policy perspective, understanding which firms and sectors disproportionately drive volatility can improve the design of targeted interventions. For instance, monetary policy may have outsized effects in sectors such as construction, while fiscal policies such as targeted infrastructure spending could be more efficient than broad-based stimulus. Moreover, antitrust and industrial policy should account for systemic risks posed by dominant firms whose shocks can ripple through the economy. Firm-level data should therefore play a central role in macroeconomic surveillance.

While our results are robust, several limitations remain. First, cross-country differences could be further explored by accounting for institutional and structural factors, including market rigidities and regulatory environments, which may influence the transmission of firm-level shocks. Second, the identification strategy for demand-side shocks—using material costs as a proxy—may not fully capture the complexity of firm-specific demand fluctuations; alternative proxies would help validate and strengthen our findings and enrich the analysis. Thirdly, our analysis acknowledges cross-sectoral differences in the impact of idiosyncratic shocks. However, fully accounting for sector-specific characteristics, including varying production technologies and market structures, remains unexplored. These heterogeneities could influence how shocks propagate within and across sectors. Future research could therefore pursue more detailed sectoral and country-specific modeling alongside the use of additional demand-side shock proxies.

Declarations

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Appendix

Table A1. Descriptive statistics for largest 50 firms, by country.

Mean value (*SD*)	Sales (in million EUR)	Material costs (in million EUR)
All countries	2212	1387
Spain	3839	2658
	(3163)	(2450)
France	7207	4410
	(9539)	(7358)
Hungary	410	265
	(450)	(385)
Italy	3263	1967
	(3505)	(2614)
Poland	1289	698
	(2445)	(1007)
Portugal	707	447
	(676)	(565)
Sweden	695	457
	(483)	(398)
Slovenia	290	195
	(285)	(228)

Source: Orbis database.

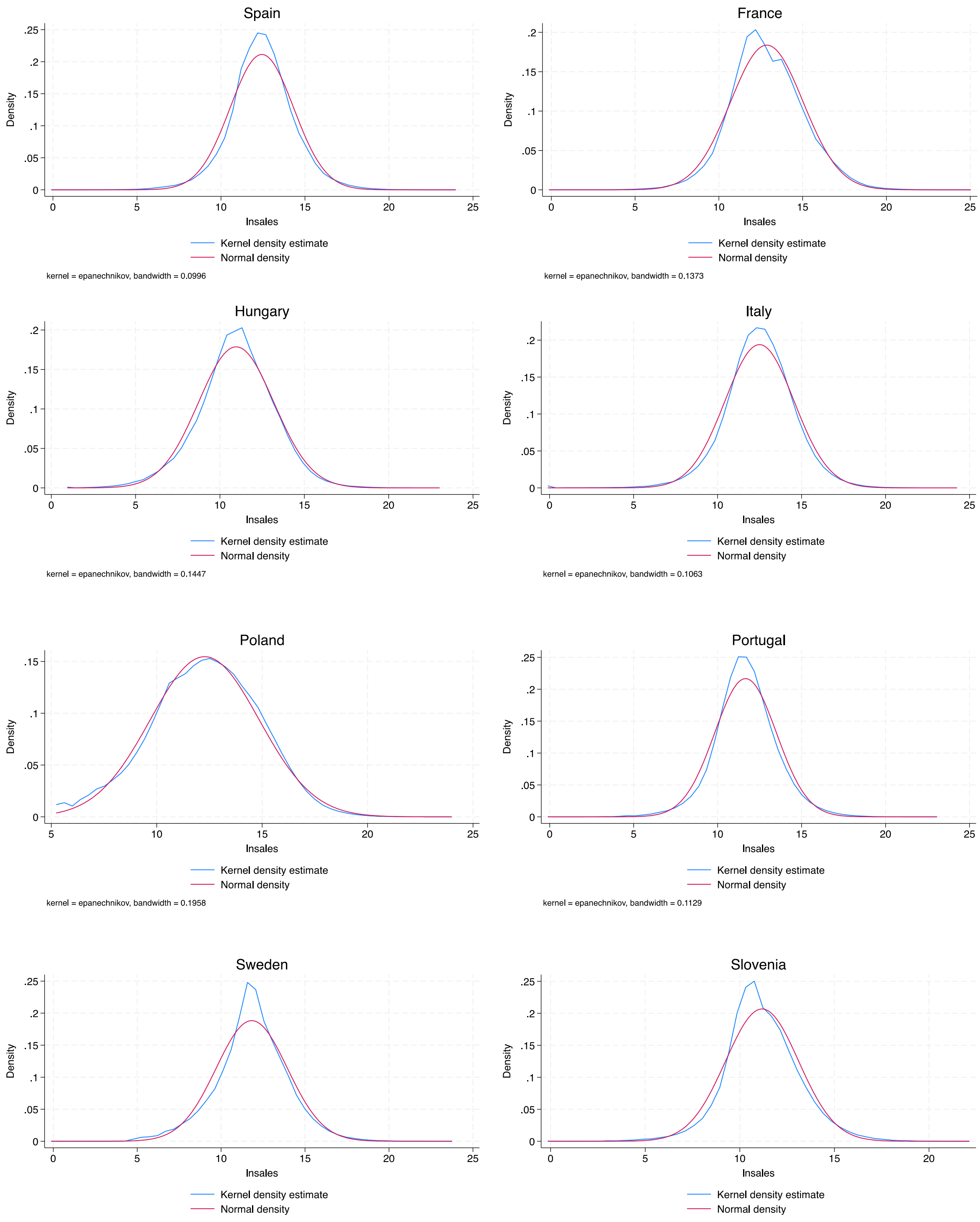

Fig. A1. Kernel density plots of log sales for 2019, by country.
Source: Orbis database.

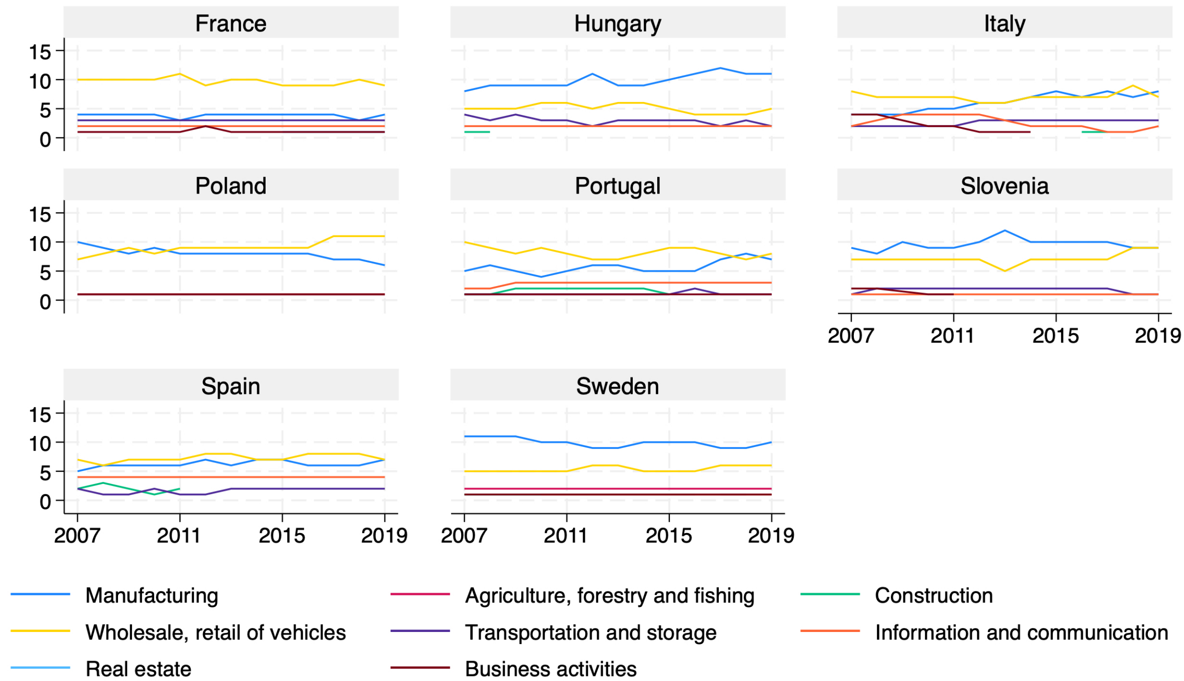

Fig. A2. Sectoral composition of the largest 20 firms over time, by country.
Source: Orbis database.

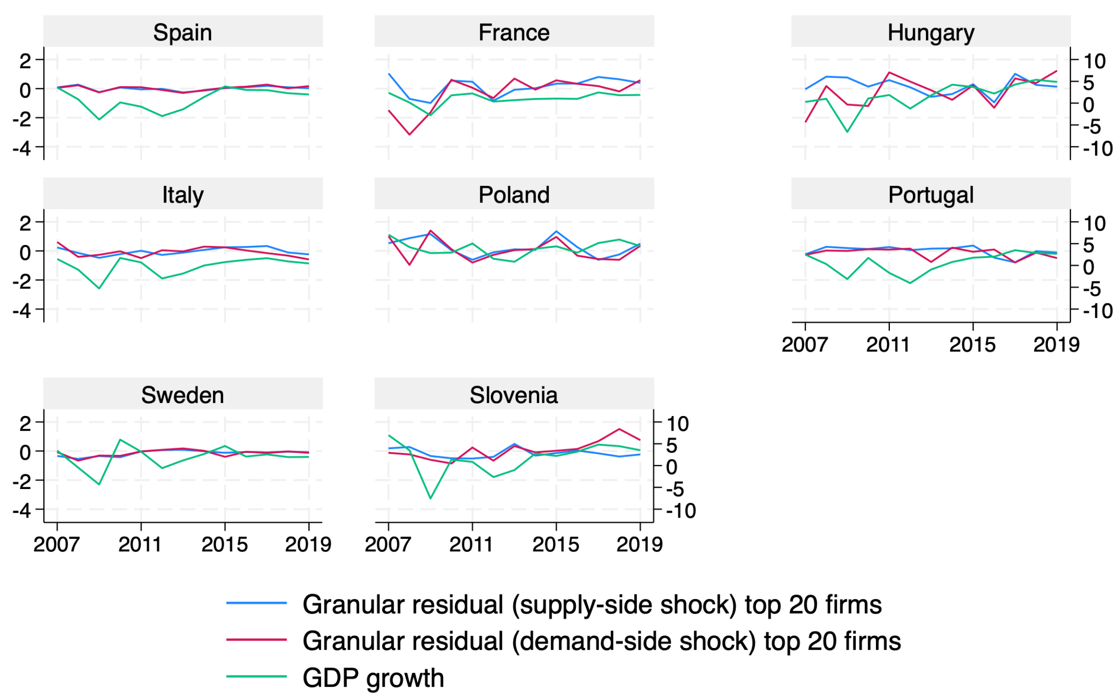

Fig. A3. GDP growth and granular residuals over time, by country.
Source: Orbis database.

Table A2. Supply-side shocks in largest 5 firms at the sectoral level, by country.

	1	2	3	4	5	6	7	8	9	10
ES	0.220***	0.416**	0.125***	−0.752***	0.352	−0.188***	−0.080**	0.320***	−0.109***	−0.916***
	(0.007)	(0.134)	(0.035)	(0.143)	(0.594)	(0.040)	(0.026)	(0.032)	(0.030)	(0.091)
FR	0.069	−0.034	0.534*	0.112	0.354	−0.195***	−1.314***	−1.201***	0.182**	0.727***
	(0.179)	(0.066)	(0.228)	(0.084)	(0.517)	(0.033)	(0.236)	(0.073)	(0.064)	(0.087)
HU	−0.154	−0.813***	0.219***	0.762***	−1.296**	−0.524***	0.916***	1.329***	−0.086	0.990***
	(0.082)	(0.221)	(0.003)	(0.110)	(0.520)	(0.040)	(0.073)	(0.034)	(0.086)	(0.119)
IT	0.869***	0.293***	0.275**	0.465***	6.318***	1.062***	−0.006	0.296***	0.258	0.500
	(0.135)	(0.051)	(0.100)	(0.016)	(0.861)	(0.038)	(0.009)	(0.051)	(0.306)	(0.295)
PL	0.025	0.640***	0.894***	1.053***	−0.743*	0.515***	0.480***	−0.334***	0.444***	1.087***
	(0.059)	(0.089)	(0.164)	(0.087)	(0.353)	(0.041)	(0.127)	(0.001)	(0.096)	(0.089)
PT	−0.381***	0.759***	−0.691***	0.668***	−1.332***	−0.077	−2.316***	−1.244***	−0.065	0.436***
	(0.040)	(0.095)	(0.016)	(0.021)	(0.264)	(0.248)	(0.650)	(0.077)	(0.062)	(0.042)
SE	0.691***	2.629***	0.436**	3.607***	1.406**	0.133	−0.203**	0.018	0.150**	1.975***
	(0.004)	(0.504)	(0.132)	(0.207)	(0.593)	(0.138)	(0.069)	(0.013)	(0.046)	(0.215)
SI	0.113	0.286***	−0.076	1.113***	−2.364***	1.879***	−0.111***	−0.313**	0.162***	0.701***
	(0.061)	(0.062)	(0.067)	(0.185)	(0.440)	(0.211)	(0.001)	(0.091)	(0.022)	(0.118)
GFC	−2.710***	−2.392***	−2.886***	−2.772***	−2.193**	−2.513***	−2.514**	−2.505***	−2.662***	−2.705***
	(0.639)	(0.615)	(0.611)	(0.742)	(0.639)	(0.688)	(0.742)	(0.639)	(0.660)	(0.708)
Const.	1.508***	1.321***	1.545***	0.973**	1.381***	1.370***	1.463***	1.784***	1.522***	1.421***
	(0.212)	(0.241)	(0.218)	(0.359)	(0.238)	(0.251)	(0.251)	(0.181)	(0.220)	(0.248)
Obs.	96	96	96	96	96	96	96	96	96	96
R^2	.463	.471	.445	.473	.531	.468	.432	.498	.421	.443

Note. Dependent variable: GDP growth. Pooled OLS estimations. Standard errors in the parentheses. GFC = global financial crisis dummy. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France. Largest firms are identified based on their lagged sales; 1—Agriculture, forestry, and fishing, 2—Manufacturing, 3—Water supply, sewerage, waste management, 4—Construction, 5—Wholesale, retail, and repair of motor vehicles, 6—Transportation and storage, 7—Accommodation and food services, 8—Information and communication, 9—Real estate, 10—Scientific technical and other business activities.
*** $p < .01$. ** $p < .05$. * $p < .1$.

Table A3. Demand-side shocks in largest 5 firms at the sectoral level, by country.

	1	2	3	4	5	6	7	8	9	10
ES	0.766***	0.675***	0.111***	−0.143**	1.358***	−0.134***	−1.923***	0.602***	−0.146***	0.061**
	(0.062)	(0.093)	(0.013)	(0.058)	(0.314)	(0.027)	(0.117)	(0.062)	(0.005)	(0.026)
FR	−0.443***	−0.274***	−0.127***	0.258	−0.778**	0.139***	1.823***	−0.626***	0.149***	0.027
	(0.087)	(0.050)	(0.022)	(0.176)	(0.241)	(0.035)	(0.196)	(0.051)	(0.004)	(0.044)
HU	−1.024***	−0.949***	0.191***	0.353***	−1.787***	−0.478***	2.502***	−0.300***	0.081***	0.034
	(0.045)	(0.165)	(0.034)	(0.049)	(0.262)	(0.001)	(0.042)	(0.049)	(0.020)	(0.035)
IT	0.014	0.036	0.125***	0.048	4.814***	−0.095*	1.911***	−0.604***	0.453***	0.093
	(0.060)	(0.061)	(0.010)	(0.132)	(0.453)	(0.041)	(0.119)	(0.054)	(0.001)	(0.083)
PL	−0.642***	−0.330**	−0.025***	0.241*	−2.033***	0.018	1.802***	−0.641***	0.266***	−0.022
	(0.006)	(0.101)	(0.005)	(0.124)	(0.168)	(0.052)	(0.152)	(0.076)	(0.026)	(0.012)
PT	−1.453***	0.037	0.017	−0.543***	−2.410***	0.085**	1.938***	−0.535***	0.072	0.170**
	(0.048)	(0.049)	(0.037)	(0.051)	(0.130)	(0.026)	(0.151)	(0.095)	(0.060)	(0.051)
SE	−0.368***	0.368***	−0.035	3.278***	0.631*	0.154**	1.591***	−0.601***	0.173***	−0.993***
	(0.048)	(0.104)	(0.054)	(0.176)	(0.293)	(0.047)	(0.015)	(0.048)	(0.002)	(0.262)
SI	−0.666***	−0.150***	−0.438***	0.577***	−2.976***	0.806***	1.470***	−0.518***	0.182***	−0.096***
	(0.069)	(0.037)	(0.022)	(0.072)	(0.190)	(0.037)	(0.042)	(0.059)	(0.007)	(0.003)
GFC	−2.794***	−2.313***	−2.368***	−2.809***	−2.310***	−2.421***	−2.495**	−2.548***	−2.552***	−2.449**
	(0.656)	(0.622)	(0.564)	(0.677)	(0.617)	(0.596)	(0.733)	(0.686)	(0.661)	(0.702)
Const.	1.427***	1.321***	1.488***	1.442***	1.532***	1.300***	1.053***	1.441***	1.493***	1.469***
	(0.207)	(0.219)	(0.195)	(0.173)	(0.235)	(0.227)	(0.270)	(0.233)	(0.220)	(0.241)
Obs.	96	96	96	96	96	96	96	96	96	96
R^2	.444	.473	.470	.496	.545	.507	.460	.432	.425	.425

Note. Dependent variable: GDP growth. Pooled OLS estimations. Standard errors in the parentheses. GFC = global financial crisis dummy. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France. Largest firms are identified based on their lagged sales; 1—Agriculture, forestry, and fishing, 2—Manufacturing, 3—Water supply, sewerage, waste management, 4—Construction, 5—Wholesale, retail, and repair of motor vehicles, 6—Transportation and storage, 7—Accommodation and food services, 8—Information and communication, 9—Real estate, 10—Scientific technical and other business activities.
*** $p < .01$. ** $p < .05$. * $p < .1$.

Table A4. Supply-side shocks in largest 3, 5, and 10 firms at the sectoral level for selected sectors, by country.

	Largest 3 firms			Largest 5 firms			Largest 10 firms		
	1	2	3	1	2	3	1	2	3
ES	0.769***	−1.044***	−2.235***	0.416**	−0.752***	0.352	0.675***	−1.021***	0.205
FR	−0.463**	0.308	2.726***	−0.034	0.112	0.354	−0.269***	0.361***	−0.236
HU	−1.137***	1.061***	1.107**	−0.813***	0.762***	−1.296**	−0.842***	1.075***	−1.141
IT	−0.194***	1.185***	11.019***	0.293***	0.465***	6.318***	−0.363**	0.421***	1.969
PL	0.318**	2.227***	1.796***	0.640***	1.053***	−0.743*	1.078***	1.857***	−0.218
PT	0.223	1.235***	0.807***	0.759***	0.668***	−1.332***	0.340***	0.709***	−1.390*
SE	0.987***	5.164***	4.066***	2.629***	3.607***	1.406**	1.391***	3.445***	2.392*
SI	−0.126***	1.830***	0.058	0.286***	1.113***	−2.364***	0.098	1.400***	−1.754*
GFC	−2.334***	−2.907***	−2.092***	−2.392***	−2.772***	−2.193**	−2.541***	−2.516**	−2.305**
Const.	1.202***	0.973***	1.428***	1.321***	0.973**	1.381***	1.290***	0.59	1.424***
Obs.	96	96	96	96	96	96	96	96	96
R^2	.452	.494	.540	.471	.473	.531	.480	.491	.492

Note. Dependent variable: GDP growth. Pooled OLS estimations. Standard errors in the parentheses. GFC = global financial crisis dummy. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France. Largest firms are identified based on their lagged sales; 1—Manufacturing, 2—Construction, 3—Wholesale, retail, and repair of motor vehicles.
*** $p < .01$. ** $p < .05$. * $p < .1$.

Table A5. Demand-side shocks in largest 3, 5, and 10 firms at the sectoral level for selected sectors, by country.

	Largest 3 firms			Largest 5 firms			Largest 10 firms		
	1	2	3	1	2	3	1	2	3
ES	0.943***	0.326***	−1.584***	0.675***	−0.143**	1.358***	0.735***	−0.607**	1.399**
FR	−0.579***	−0.074	1.909***	−0.274***	0.258	−0.778**	−0.287***	0.494***	−1.344**
HU	−1.057***	−0.374***	0.839***	−0.949***	0.353***	−1.787***	−0.805***	0.662**	−2.088***
IT	−0.533***	−1.001***	6.539***	0.036	0.048	4.814***	−0.707***	0.770***	0.850
PL	−0.718***	0.069	1.208***	−0.330**	0.241*	−2.033***	−0.207	1.146***	−1.055***
PT	−0.316***	−0.828***	−0.121***	0.037	−0.543***	−2.410***	−0.097	0.275*	−2.300***
SE	0.357***	4.122***	3.633***	0.368***	3.278***	0.631*	1.101***	2.074***	1.157**
SI	−0.526***	0.283	−0.171	−0.150***	0.577***	−2.976***	−0.326**	0.825***	−2.662***
GFC	−2.388***	−2.700***	−2.192***	−2.313***	−2.809***	−2.310***	−2.496***	−2.809***	−2.517***
Const.	1.355***	1.763***	1.385***	1.321***	1.442***	1.532***	1.343***	1.056**	1.714***
Obs.	96	96	96	96	96	96	96	96	96
R^2	.460	.533	.540	.473	.496	.545	.520	.464	.505

Note. Dependent variable: GDP growth. Pooled OLS estimations. Standard errors in the parentheses. GFC = global financial crisis dummy. Reported coefficients are taken directly from results; to obtain the coefficient for, e.g., France, one needs to sum up the coefficients for Spain and France. Largest firms are identified based on their lagged sales; 1—Manufacturing, 2—Construction, 3—Wholesale, retail, and repair of motor vehicles.
*** $p < .01$. ** $p < .05$. * $p < .1$.