Bank of Russia

IDIOSYNCRATIC SHOCKS: ESTIMATION AND THE IMPACT ON AGGREGATE FLUCTUATIONS

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ABSTRACT

Recently, economic granularity has been the focus of researchers' attention. Latest empirical works evaluate the granularity of various economies in terms of whether shocks to individual companies can affect volatility of macroeconomic variables. Studies of developed countries show that a large part of aggregate fluctuations arises from idiosyncratic shocks to companies because of their size or close linkages between them. Using the microdata of Russian firms on sales over the period from 1999 to 2017, we test the hypothesis that the Russian economy is granular. Here we found that idiosyncratic shocks contribute significantly to total sales volatility. It was also revealed that the effect of linkages is more important in aggregate volatility estimation, but not for the top-100 largest firms. These findings are important for understanding business cycle drivers and for estimation the impact of macroeconomic policies.

Keywords: firm-level dynamics, granular residuals, idiosyncratic shocks, aggregate fluctuations, industrial production.

JEL classification: D20, E32, L14.

INTRODUCTION

The predominant macroeconomic theory has long assumed that business–cycle fluctuations are the results of aggregate macroeconomic changes. Firm-specific or idiosyncratic shocks in these models average out, they have a negligible effect at the aggregate level (Lucas, 1977). However, there is some theoretical evidence of the important role of idiosyncratic shocks in explaining aggregate fluctuations, which is also confirmed by the real evidence in developed economies. For instance, according to the Organization for Economic Cooperation and Development (OECD (2004)) in 2000 Nokia contributed 1.6 percentage points of Finland's GDP growth. (Gabaix, 2011).

Researchers have different explanations for the effects of firm-level shocks and sectoral shocks on volatility of macro variables. Some researchers suppose that firms' shocks can have an impact due to the firm size distribution, i.e. when such distribution is fat-tailed. In that case, shocks to large firms do not average out and instead output or productivity shocks to large firms have a potential to drive aggregate volatility. Another perspective of research argues that aggregate fluctuations can arise from firm-level shocks because of interconnectedness between firms or sectors. If sectors or firms are closely connected with others through intermediate consumption or common labour markets, these linkages can distribute firm-specific shocks more intensively across the economy.

In this paper, we test the hypothesis that firm-level shocks can generate shocks affecting GDP and, through equilibrium, all other firms. Hence, we assume that economic fluctuations are caused not only by shocks in monetary, fiscal, or macroprudential policies, but also by substantial fluctuations in individual firms. This effect is called the granular hypothesis, which states that firm-level shocks do not average out at the aggregate level, but can become significant drivers of business-cycle fluctuations.

In recent years, modern economies are mainly dominated by large firms whose idiosyncratic shocks may potentially have a non-trivial effect on production dynamics. In US, the share of sales of the top-100 firms account for more than 30% of GDP since 2000 (Gabaix, 2011). A similar share for the euro area countries amounted to about 28.5%[1] of GDP over the period 1999-2013 (Ebeke & Eklou, 2017). According to Russian data, the average share of sales of the top-100 non-financial companies[2] in Russia's GDP was about 20% over the period of 1999–2016 (Figure 2). Taking into account the extractive sector the ratio increases to 50% of GDP (Figure 1). Thus, a relatively small number of large Russian firms represent a significant part of the macroeconomic activity. We may assume that in the

[1] Non-financial companies, except firms doing business in the mining industry or the energy market.
[2] Excluding companies related to the mining, electric power and fuel industries. Source: SPARK accounting database.

Russian economy a certain group of firms can potentially affect business activity. An analysis of such shocks can be helpful for forecasting and better understanding the drivers of economic performance.

Figure 1. Sales share of the top-100 non-financial firms, % of GDP

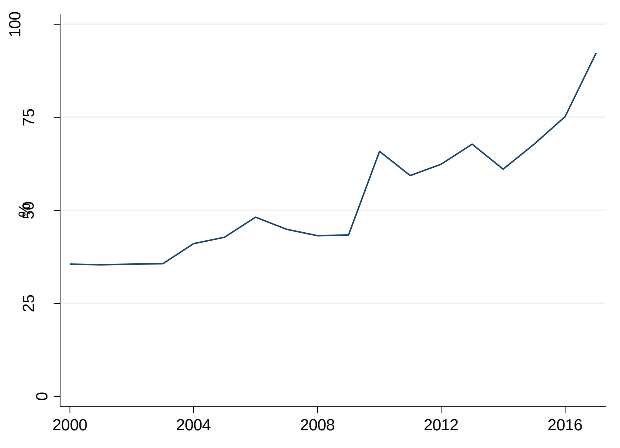
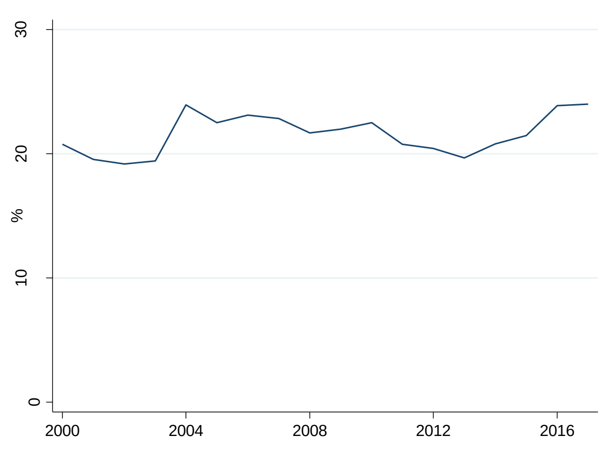


Figure 2. Sales share of the top-100 non-financial firms, excluding mining and energy enterprises, % of GDP



Sources: author's calculations based on SPARK data, Rosstat.

There is a sufficient amount of empirical research devoted to the study of this hypothesis in various countries. Their authors use different approaches to the estimation of idiosyncratic shocks, which in some cases shows opposite results. So, Gabaix (2011) found that shocks to the 100 largest US firms account for about 1/3 of the variations in output dynamics. For Canada, a similar analysis also provided important results: Karasik et al. (2016) showed that large firms' shocks account for 46% of variation in aggregate output growth and for 37% of investment growth variations. Ebeke and Eklou (2017) evaluated the effect of idiosyncratic shocks for the eurozone countries and found that large companies account for about 40% of GDP volatility in the respective countries. Stella (2015), however, used a dynamic factor model based on US quarterly data for identification. As a result, they did not find any confirmation of the granular hypothesis: after proper controlling for aggregate shocks, the idiosyncratic component is too insignificant to account for business cycle fluctuations in the US.

There is still little empirical evidence on the role of individual firms in explaining aggregate fluctuations in emerging markets. This type of analysis based on Russian data can be useful for forecasting and more detailed analysis of factors affecting the current production dynamics and other macroeconomic variables. Moreover, it is essential to examine our findings in greater details so as to disentangle the economic mechanisms at work. A study of cross-sector irregularities and linkages between industries and firms can provide additional information on the nature of such shocks.

In this paper, we evaluate the effects of firm-level shocks on aggregate output volatility using data from Russian companies. We relied on a model based on the approach proposed by di Giovanni et al.

(2014), with some modifications. We show that idiosyncratic shocks prevail in the variation in aggregate volatility of total output, while macro-sectoral shocks are dominant for the 100 largest companies. An idiosyncratic component is almost entirely related to the linkage effect, but not for the top-100 companies.

The remainder of the paper is organized as follows. Section 1 provides a literature review summarizing the results obtained for other countries. Section 2 describes our underlying model. Section 3 presents data. Section 4 discusses empirical results and presents some practical implications of the results. The paper concludes with Section 5.

1. LITERATURE REVIEW

Recently, research papers have focused a lot on microeconomic foundations behind macroeconomic models. In particular, microeconomic foundations are referred when studying the nature of business cycles and macro fluctuations. One of the research areas is the so-called granular economy suggesting that firm-level volatility may affect dynamics of macroeconomic indicators. Some papers analyse how individual firms' shocks can affect the aggregate fluctuations in the economy and provide theoretic evidences for this problem (Gabaix, 2011; Karasik et al.,2016; Ebeke and Eklou K. M., 2017). The authors found empirical evidence for their hypotheses suggesting that firm-level shocks contribute considerably to business cycle fluctuations in markets dominated by large firms (granular economies). A parallel line of research addresses the impact of sectoral fluctuations on business cycles. The authors claim that idiosyncratic shocks to economic sectors can have a significant impact on the macro fluctuations (Horvath, 1998; Foerster et al., 2011; Acemoglu et al., 2012). These papers suggest that a relatively small number of sectors can lead to macro fluctuations. Therefore, to analyse the reasons for aggregate volatility, it is essential to understand what causes volatility in individual economic sectors.

The conventional assumption that firm-level shocks cannot have any influence is based on the law of large numbers. If individual shocks are independent, aggregate volatility will be proportional to $1/\sqrt{\mathrm{N}}$, where N is the number of firms in the economy. Accordingly, as $\mathrm{N} \rightarrow \infty$, shocks to individual firms will have very small effect on economic volatility. But Gabaix (2011) showed that if a firm size distribution has fat tails and is based on a power-law distribution, the central limit theorem does not work. In this case, being affected by idiosyncratic shocks, the volatility of macro variables will decline more slowly, at a rate of $1/\ln \mathrm{N}$. Thus, if an economy has large companies, their productoin or productivity shocks may translate into GDP volatility. Likewise, Karasik et al. (2016) test the granular hypothesis using Canada firm-level data. The authors analysed how large firms' shocks affected the volatility of output, investments and employment in the manufacturing sector and found that idiosyncratic shocks to major companies are statistically significant to explain variations in sales and investments.

Another perspective of research explains the granularity in the economy through the relations between companies or industries, as some sectors or firms use the output of other sectors as intermediate goods in their production. Foerster et al. (2011) consider the decomposition of industrial production dynamics into components: aggregate and specific sectoral shocks. The factor model showed that all fluctuations in industrial production can be attributed to macroeconomic factors. However, using multisector model the authors found that industry-specific shocks explain more than half of industrial production variation after 1987. Acemoglu et al. (2012) showed that sectoral shocks account for a significant part of macro volatility if there are strong linkages between sectors. In addition, not only linkages are important, but asymmetries in such networks. Otherwise, the aggregate shock is a symmetric function of the shocks in each sector. In fact, the interconnections between sectors are very asymmetric. Therefore, the authors point out that the decline rate of volatility of macro variables directly depends on cross-sector networks. If the economy shows any heterogeneity in terms of the input-output structure or if any sectors in the supply chains play a more important role, the effect of microeconomic shocks will significantly affect macro volatility.

The paper by Giovanni et al. (2014) is a combination of the above approaches to explaining the channels of the impact of companies’ shocks on macro volatility. Similar to other research, an analysis of the impact of idiosyncratic shocks demonstrated their significance in determining aggregate fluctuations. Moreover, the authors suggest that there are two mechanisms for how firms translate their shocks into aggregate volatility. The first channel, as in the paper by Gabaix (2011), suggests that idiosyncratic shocks to firms are considerable when the central limit theorem does not work. The second mechanism implies that aggregate fluctuations are caused by idiosyncratic shocks because of networks existing between companies and sectors in the economy. The authors emphasise the importance of analysing this channel as standard macroeconomic models suggest that correlation between firms reflects only a response to macroeconomic and sectoral shocks. Decomposition showed that, firm linkages are more important as the first mechanism of influence on aggregate fluctuations. In addition, the article shows the need to expand the model by including the multiplicity of a firm's destinations, which allows assessing the decomposition of firm-level shocks: common shocks to all firms and specific shocks to a certain market. The second component accounts for the largest part of the variation at the firm level. There are several other articles on this issue. Below are the key quantitative results of the idiosyncratic shocks’ estimates for different countries (Table 1). They show that for many countries the granular hypothesis has been more or less confirmed.

Table 1. Key findings of granularity for other countries

Authors	Country	Period	Main results
Industry level			
Horvath (1998)	USA	1947–1989	80% of GDP volatility is accounted for by independent shocks to individual industries
Foerster A. T. et al. (2011)	USA	1972–2007	After controlling for sector linkages, industry-specific shocks explain about 20% of industrial production variations prior 1987 and 50% – after 1987
Acemoglu D. et al. (2012)	USA	1972–2002	If there is significant asymmetry in the roles that sectors play as suppliers to others, sectoral idiosyncratic shocks contribute to aggregate volatility
Atalay (2017)	USA	1960–2013	Industry-specific shocks account for at least half of aggregate volatility
Firm level			
Gabaix X. (2011)	USA	1951–2008	Top-100 firms account for about 1/3 of GDP volatility
Di Giovanni J., et al. (2014)	France	1990–2007	The firm-specific component contributes substantially to aggregate sales volatility, mainly due to the linkages between firms
Stella A. (2015)	USA	1962–2011	After proper controlling for aggregate shocks, idiosyncratic component has little explanatory power in U.S. business cycle fluctuations
Friberg R., Sanctuary M. (2016)	Sweden	1997–2008	Sector-destination and firm-specific shocks account about equally for aggregate sales volatility
Karasik L., et al. (2016)	Canada	2000–2012	Idiosyncratic shocks to large firms can explain 23-46% and 15-40% of fluctuation in total output and investments respectively.
Ebeke M. C. H. and Eklou K. M. (2017)	EU countries	1998–2013	40% of the variance in GDP can be explained by idiosyncratic shocks to large firms
Fornaro P., Luomaranta H. (2018)	Finland	1998–2013	57 largest firms explain around one third of the variation in monthly economic activity
Gnocato N., Rondinelli C. (2018)	Italy	1999–2014	Idiosyncratic TFP shock accounts for around 30% of aggregate TFP volatility
Blanco-Arroyo O., et al. (2018)	Spain	1995–2016	Granular residuals explain approximately 45% of variations in GDP growth

2. METHODOLOGY

To identify a company's idiosyncratic shock and estimate its effect on volatility of macro variables, we use the standard approach described in research papers (Gabaix, 2011; Giovanni et al., 2014; Karasik et al., 2016; Gnocato and Rondinelli, 2018).

We will analyse the economy with n firms. Firm's growth rate is defined as $\gamma_{\mathrm{i,t}} = \log Y_{\mathrm{i,t}} - \log \mathrm{Y}_{\mathrm{i,t-1}}$, where $\mathrm{Y_i}$ is the variable of interest to us, here it is a firm's output.

In this case, an idiosyncratic shock implies a shock to a firm's output that is not caused by macroeconomic fluctuations or sectoral shocks that is a change in output that does not affect simultaneously all firms in the economy or the entire sector. Thus, we show the actual production growth rate of a firm as the sum of the idiosyncratic component and the general component, which can be described as a sum of macroeconomic and sectoral shocks.

$$\gamma_{it} = \delta_{st} + \varepsilon_{it} \quad (1)$$

Here we calculate the general component δ_{st} as the average growth rate of sales for sector s over a period t. Thus, the idiosyncratic shock $\varepsilon_{\mathrm{it}}$ at t is the deviation of actual sales growth from the average across the sector. Formally, we estimate the regression model of sales growth rates on a number of sectoral dummy variables. From this model, we determine the idiosyncratic shocks (or granular residuals).

Next, according to Gabaix (2011), we construct the granular shock as the weighted average sum of idiosyncratic shocks calculated at the previous stage:

$$\Gamma_t^* = \sum_{i \in K} \frac{Y_{i,t-1}}{Y_{t-1}} \varepsilon_{it} \quad (2)$$

where K is the number of firms for which we calculate granular shock. Gabaix (2011) takes the value K as a relatively small number of large firms ($K = 100$), suggesting that macroeconomic shocks affect large and small companies in different ways. Giovanni et al. (2014) build macroeconomic and idiosyncratic shocks using data from all companies. Karasik et al. (2016) calculate the granular residuals for analysis taking 10 largest firms and all companies.

According to the granular hypothesis, this indicator should affect the volatility of macro variables. For this purpose, we need to measure how much of the total GDP variation is accounted for by the granular residual ($\gamma_{Yt} = \mu \Gamma_t^*$). For this we build a regression model of the chosen macro variable for granular shock.

Let Z_t be the growth rate of the macro variable selected for analysis, here it is GDP. Then we estimate the explanatory power of granular shock using the following model:

$$Z_t = \beta_0 + \beta_1 \Gamma_t^* + u_t \quad (3)$$

R^2 of this equation will show the contribution of granular shock to volatility of the macro variable.

For a more detailed analysis of granularity and impact channels, we can represent the aggregate growth rate as follows:

$$\gamma_{Yt} = \sum_i \left(\frac{Y_{i,t-1}}{Y_{t-1}}\right)\gamma_{it} == \sum_{s\in I} w_{s,t-1}\delta_{st} + \sum_{i\in N} w_{i,t-1}\varepsilon_{it} \quad (4)$$

where $w_{s,t-1}$ is the share of sector s in the total output, and $w_{i,t-1}$ is the share of a firm i in the total output.

In this case, the decomposition of the variation in a firm's growth rate looks as follows:

$$\sigma_{Yt}^2 = \sigma_{It}^2 + \sigma_{Ft}^2 + COV_t \quad (5)$$

where

$\sigma_{It}^2 = Var\left(\sum_{s\in I} w_{s,t-1}\delta_{st}\right)$ – macro-sectoral volatility;

$\sigma_{Ft}^2 = Var\left(\sum_{i\in N} w_{i,t-1}\varepsilon_{it}\right)$ – firm-specific volatility;

$COV_t = Cov\left(\sum_s w_{s,t-1}\delta_{st}, \sum_i w_{i,t-1}\varepsilon_{it}\right)$ – covariance of the shocks from different levels of aggregation.

To identify the channels for firms’ contribution to aggregate fluctuations, idiosyncratic volatility can be decomposed into the direct effect and the linkage effect between firms:

$$\sigma_{Ft}^2 == \underbrace{\sum_i w_{i,t-1}^2 Var(\varepsilon_{it})}_{Direct\ effect} + \underbrace{\sum_{i\neq j}\sum_i w_{j,t-1}w_{i,t-1}Cov(\varepsilon_{it},\varepsilon_{jt})}_{Link\ effect} \quad (6)$$

The first element is a sum of the variances of the individual shocks. We will consider this as a direct effect. As mentioned above, according to Gabaix (2011), if the size distribution of firms is fat-tailed (i.e. when an economy has very large firms), idiosyncratic shocks do not wash out at the aggregate level.

If we assume that companies’ shocks are independent and equal, then equation (6) will be as follows:

$$\sigma_{Ft}^2 = \sigma^2 \sum_i \left(\frac{Y_{it}}{Y_t}\right)^2 = \sigma^2 \cdot H_t \quad (7)$$

where H_t – the Herfindahl index for a given economy. The more fat-tailed is the firm size distribution, the larger will be the Herfindahl index, the more concentrated will be the economy and the greater will be the aggregate volatility generated by idiosyncratic shocks.

The second term in equation (6) reflects comovements between firms' outputs, i.e. covariances of shocks across firms. This correlation arise from existing linkages through the input structure and intermediary consumption or through the common labour market. In this case, the shocks to one firm will drag the output dynamics of other firms related with the first one.

According to traditional theories, the first term will approach zero in case of a large number of firms. Standard models also do not cover the effect of linkages, as it is assumed that covariance between firms is the result of general macro- or sectoral shocks. We will also identify whether these idiosyncratic shock transmission channels are typical for Russian companies and to what extent.

3. DATA AND DESCRIPTIVE STATISTICS

In this paper, we use the annual SPARK databases for the period 1999–2017. The number of firms included in the sample ranged from 36,000 in 1999 to 107,000 in 2017. The sample represents 59 types of activities according to the Russian National Classifier of Economic Activities (OKVED). We did not include in our sample observations where:

- sales growth rates exceeded 1,000%;
- negative assets;
- total liabilities (overall long- and short-term liabilities) less than zero;
- OKVED Codes 96, 97 and 99[3];
- missing values in sales.

In our analysis, we will use the firm's revenue growth rate as the output value. In a research by Gabaix (2011), Castro, Clementi and Lee (2013), Ebeke M. C. H. and Eklou K. M. (2017), and Gnocatto and Rondinelli (2018), idiosyncratic shocks were calculated based on firms' productivity, namely TFP. SPARK does not contain accurate data on the number of employees. Therefore, similarly to Giovanni et al. (2014), Friberg R. and Sanctuary M. (2016), and Karasik L. et al. (2016), we use sales or revenue data.

All data were converted into real values using Rosstat producer price indices (three-digit OKVED codes for industrial production sectors), and other activities were converted using value added deflators, since there were no data on producer price indices for them.

Below are descriptive statistics on sales growth rates at firms' level (Table 2). The data show that the average of individual growth rates (6.2%) is less than the average aggregate growth rate of 8.0%. This means that small firms grow more slowly than large ones. Giovanni et al. (2014) and Friberg (2016) obtained opposite results. For an average firm, its growth volatility will be 0.86. The table also provides information on firms' volatility by quantiles (here the size implies the sales value). Smaller firms are much more volatile than firms in the upper quantiles. However, the largest firms (top-100) are

[3] SPARK contains 341 companies with these codes, 332 of which do not have any sales values in 1999-2017. After dropping the firms with gaps and with less than 2 observations, there remained one firm with Code 96 and five firms with Code 99, which is not enough for calculation of the average growth rate and idiosyncratic shocks.

characterised by a higher variance, which can increase the direct effect of idiosyncratic shocks (see equation (6)).

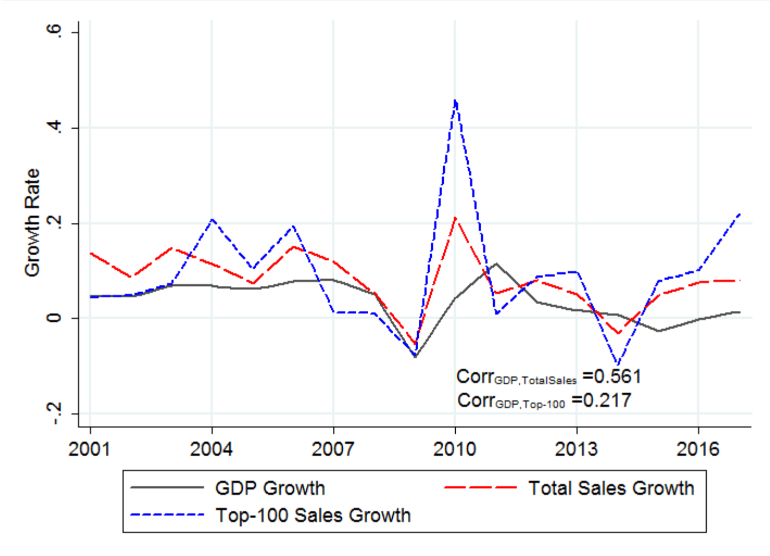
The representativeness of the data used demonstrates Figure 3. The growth rate of aggregate sales in the sample and GDP growth rate show approximately the same trend. Thus, we can conclude that the data are representative enough.

Table 2. Descriptive statistics for sales growth rates

Average aggregate growth rate	0.0802
Mean of individual growth rates	0.0624
Standard deviation of sales growth rate	0.8676
0–25th percentile by size	1.1484
26–50th percentile by size	0.7753
51st–75th percentile by size	0.7165
76–100th percentile by size	0.7259
Top-100	0.8437
Top-10	0.8014

Source: author's calculations.

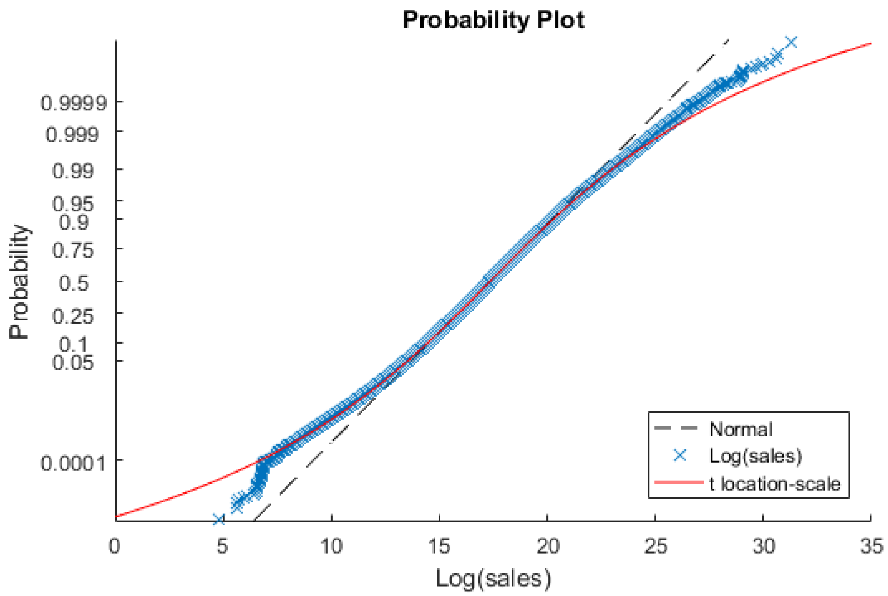
Figure 3. Aggregate sales growth rate, sales growth rate for the top-100 firms and GDP growth rate



Sources: author's calculations, Rosstat.

For further analysis, it is necessary to verify the key assumption underlying Gabaix's approach (2011), according to which the firm size distribution is not normal, but rather a fat-tailed, i.e. this is a power-law distribution. If the distribution of Russian companies by sales is power-law, we can assume that for the Russian economy idiosyncratic shocks can be the drivers of aggregate volatility. Figure 4 shows the firm distribution of the variable of the logarithm of sales, where we see that the distribution tails (both right and left) substantially differ from the normal distribution chart.

Figure 4. Firm size distribution of Russian firms by sales and the normal distribution



Source: author's calculations.

Next, we will formally test whether our data follow the power-law distribution described by Gabaix (2011) in the article. The power law implies that there is a significant number of very small events and very few large ones and, in addition, such distribution characterises the exponential relationship between the event scale and its frequency. Formally, the variable X is subject to a power-law distribution if the distribution function is as follows:

$$P(X \geq x) \simeq kx^{-\zeta} \quad (8)$$

An example of a power-law distribution is Zipf's Law, where ζ (power-law distribution exponent) is close to unity. This law implies that a firm's size will be inversely proportional to its rank, where rank implies the firm's serial number in a sample ranked by sales. Mathematically, Zipf's law can be written as follows:

$$rank = N \cdot P(X \geq x) = Nkx^{-\zeta} \quad (9)$$

Finding the logarithm of the previous equation, we get:

$$\ln rank = K - \zeta \ln x \quad (10)$$

To conclude about the power-law distribution, we estimate the parameter ζ. In the article, Gabaix (2011) proves that, if the distribution is power-law, the exponent will be $1 \leq \zeta < 2$. Gabaix and Ibragimov (2011) show how this parameter can be estimated using the ordinary least squared method. They offer the following modification:

$$\ln(rank - \frac{1}{2}) = \alpha - \zeta \ln x + \varepsilon \quad (11)$$

Below are estimates of the power-law distribution exponent for the 1000 largest firms by sales in Russia, where x is the amount of real sales for firm i.

Table 3. Estimates of the power-law distribution exponent for 1000 largest Russian firms by sales

	2000	2001	2002	2003	2004	2005	2006	2007	2008
Coefficient ζ	0.94	1.02	1.05	1.04	1.06	0.72	0.65	1.05	1.04
s.e.	0.04	0.05	0.04	0.06	0.06	0.06	0.06	0.06	0.05
R^2	0.84	0.82	0.85	0.83	0.85	0.61	0.52	0.85	0.80

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Coefficient ζ	0.82	0.94	0.95	1.09	1.02	0.83	1.06	0.81	0.98
s.e.	0.06	0.05	0.05	0.03	0.05	0.06	0.03	0.07	0.05
R^2	0.66	0.75	0.80	0.93	0.88	0.65	0.92	0.56	0.79

Source: author's calculations.

The results show that the parameter ζ exceeds 1 for most years, which confirms our hypothesis that the sales data of Russian firms are subject to a power-law distribution. As a result, we may make a guess that the Russian economy is granular.

4. EMPIRICAL RESULTS

4.1 Model results

4.1.1 Testing the granular hypothesis using the methodology of Gabaix (2011)

This section describes the results of assessing the impact of idiosyncratic shocks on GDP volatility. We obtained these results using the identification method proposed by Gabaix (2011). Using equation (1), we define idiosyncratic shocks as the deviation of a firm's actual growth rate from the common output shock. In this research, we considered two variables as a common shock or macro-sectoral shock: the annual average output growth rate t and the annual average growth rate t for the industry s. Similarly to Gabaix (2011), the granular residual (equation (2)) was calculated for all companies and for the top 100 companies. Granular residuals were calculated as follows Table 4. Industries in this case were defined by two-digit OKVED codes. All series that we analyze are stationary.

Table 4. Summary of granular residuals measures

	Firms for granular residuals calculations (K)	Macro-sectoral shock (δ_t)
G1	All firms from sample	Average sales growth rate over year
G2	All firms from sample	Average sales growth rate over year and sector
G3	Top-100 for each year by t-1 sales	Average sales growth rate over year
G4	Top-100 for each year by t-1 sales	Average sales growth rate over year and sector
G5	All firms from sample	Average sales growth rate over year and sector
G6	Top-100 in each year and in each sector by t-1 sales	Average sales growth rate over year and sector
G7	Top-100 in each year and in each sector by t-1 sales	Average sales growth rate over year and sector for top-100

Table 5 contains the results of estimation the granular shock impact, calculated in various ways, on the GDP growth rate:

$$GDP\_growth_t = \beta_0 + \beta_1\Gamma_t + u_t \quad (12)$$

R^2 in this regression equation shows the share of the GDP growth rate variation that can be attributed to granular shocks.

Table 5. Explanatory power of the granular residuals

	Dependent variable: real GDP growth rate							
	G1	G1	G2	G2	G3	G3	G4	G4
Γ_t	-0.202* (0.114)	-0.176 (0.119)	-0.160 (0.102)	-0.128 (0.107)	-0.303 (0.178)	-0.423** (0.173)	-0.169 (0.155)	-0.220 (0.166)
Γ_{t-1}		-0.122 (0.159)		-0.150 (0.183)		-0.353 (0.224)		-0.209 (0.288)
_cons	0.014 (0.018)	-0.004 (0.026)	0.014 (0.020)	-0.012 (0.035)	0.028** (0.013)	0.001 (0.018)	0.030* (0.015)	0.007 (0.030)
N	18	17	18	17	18	17	18	17
R^2	0.165	0.220	0.133	0.176	0.154	0.323	0.069	0.115
R^2_{adj}	0.113	0.109	0.078	0.058	0.101	0.227	0.011	-0.011

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*
Source: author's calculations.

We can see that almost all the coefficients are not statistically significant and do not show any positive correlation, unlike the correlations shown by the authors in other articles. This can be explained by a small number of observations of annual GDP and data on sales of firms, in contrast to other countries. Moreover, the 2009 crisis is also part of our sample, which may bias the coefficient estimates. Indeed, after adding the dummy variable for 2009, the estimates changed, the coefficients in case of granular shocks became insignificant, R^2 grew substantially, and the dummy variable was statistically significant at the level of 1%. The results are provided in the Appendix (Table 9). In addition, it should be noted that Gabaix (2011) did a lot of work with outliers, namely he completely excluded the oil and gas sector from the sample, as well as the energy and financial industries. In our opinion, oil and gas companies should not be omitted when analysing Russian data, since this sector accounts for a substantial part of Russia's business activity.

Table 6. Explanatory power of the granular residuals, industry panel

Dependent variable: Real VAD growth rate			
	G5	G6	G7
Γ_{jt}	-0.036 (0.041)	-0.474 (0.763)	-0.767 (1.083)
_cons	0.043*** (0.010)	0.048*** (0.008)	0.049*** (0.007)
N	728	728	728
R^2	0.001	0.001	0.001
R^2_{adj}	-0.001	-0.001	-0.001

Standard errors in parentheses
** p<0.05, ** p<0.01, *** p<0.001*
Source: author's calculations.

We also estimated a similar model in which the gross value added (VAD) at fixed prices by type of economic activity is the dependent variable, and the granular shock Γ_{jt} is the sum of firms' idiosyncratic shocks from equation (1) for individual sectors.

$$VAD\_growth_{jt} = \beta_0 + \beta_1 \Gamma_{jt} + u_{jt} \quad (13)$$

The time period in this case is shorter: 2004–2017. The equation was estimated using a pooled OLS. The results are presented in Table 6. Sector aggregation granularity did not show significant results. The dynamics of gross value added by economic activity cannot be explained by a granular shock to Russian companies. This is probably due to the specifics of VAD observations and its comparison with the dynamics of firms' sales.

4.1.2 Estimation of contributions of the idiosyncratic component to aggregate volatility

Previous results did not provide any confirmation of the granularity of the Russian economy. In the next step, we construct idiosyncratic shocks using a different identification following Giovanni et al. (2014). We analyse the sales decomposition according to equation (1). The individual growth rates of firms are presented as the sum of two components: idiosyncratic and macro-sectoral.

The idiosyncratic component was calculated in two ways:

1) the deviation of the individual growth rate of the firm from the average growth rate of the industry for each year (simple model)
2) part of the growth rate that is not related to factors depending on the firm's characteristics (model with control variables).

As control variables, we took:

- size (dummy variables by assets)
- age (dummy variable is 1, if the age is over 5 years; or equals 0 otherwise)
- debt ratio (dummy variable for quartiles of the debt-to-sales ratio).

Idiosyncratic shocks that we used in the models are calculated by:

1) all companies from the sample
2) top-100 companies (for each year we select the top-100 firms by sales if company is older than 5 years). We have chosen 290 unique companies.

Table **7** shows descriptive statistics of the actual growth rates of firms' sales and components resulting from decomposition. The last column of the table shows the correlation between each component and actual sales growth. High correlation values (0.98, 0.80 and 0.80, respectively) indicate that sales growth variation is dominated by the firm-specific component, rather than macro-sectoral shocks. The standard deviation of a firm-specific component is almost the same as the standard deviation of the actual sales growth rate. At the same time, the macro-sectoral component is quite stable. These results show that most of the shocks hitting by firms are idiosyncratic, not macro or sectoral, which is consistent with studies for other countries (Haltiwanger, 1997; Castro, Clementi and Lee, 2013; Giovanni et al., 2014).

Table 7. Summary statistics and correlations of actual, macro-sectoral and firm-specific components

	Whole economy (simple model)			
	Obs.	Mean	St.Dev.	Corr.
Actual	1 279 017	0.0548	0.8202	1.0000
Firm-specific	1 279 017	-0.0085	0.8059	0.9829
Macro-sector	1059	0.0635	0.1513	0.1854
	Top-100 companies			
	Obs.	Mean	St.Dev.	Corr.
Actual	1 800	-0.0358	0.5320	1.0000
Firm-specific	1 800	-0.1018	0.5107	0.8028
Macro-sector	317	0.0660	0.3280	0.3720

Source: author's calculations.

However, a high correlation between an idiosyncratic component and actual growth rate at the micro level does not mean that the economy is granular or that idiosyncratic shocks will explain volatility of indicators at the aggregate level. To that end, it is necessary to take into account the size of firms, namely the identified components must be aggregated (equation 4)) using some weights.

After aggregation, we calculated the variation in each component in accordance with equation (5). Table 8 and Figure 5 contain the main results of this decomposition. Figure 5 shows the estimated volatility of the total output by firms σ_{Y_t} and the estimated volatility of its components: the idiosyncratic σ_{F_t} and macrosectoral σ_{I_t} shocks for the entire sample (grey lines), for the top-100 firms (red lines) and for the entire sample, but using control variables (blue lines). The charts also show 95% confidence intervals for variation which were estimated both analytically and bootstrapping. Table 8 shows the average values of the estimated standard deviations (σ_{Y_t}, σ_{F_t}, and σ_{I_t}) and the respective values of standard deviations (equation (14)) for the entire sample, for the top-100 firms and for the entire sample using control variables.

$$Rel.St.Dev^2 = \frac{\sigma_{Ft}^2}{\sigma_{Yt}^2} = \frac{Var\left(\sum_{i \in N_j} w_{i,t-1}\varepsilon_{it}\right)}{\sigma_{It}^2 + \sigma_{Ft}^2 + COV_t} \quad (14)$$

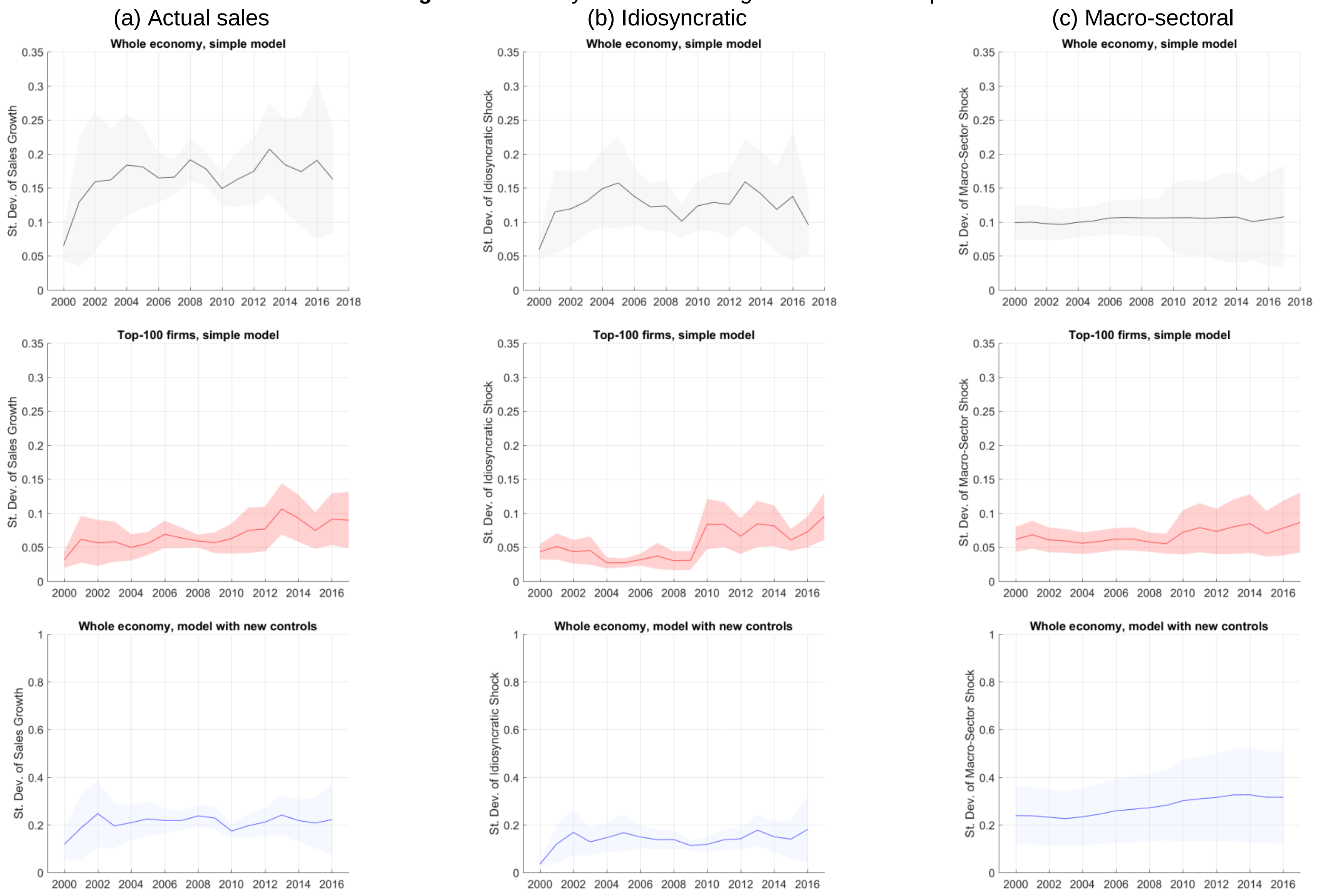
Table 8. The aggregate impact of firm-specific and macro-sectoral components on aggregate volatility

	Whole economy		Whole economy (controls)		Top-100 firms	
	St.Dev.	Relative St.Dev.	St.Dev.	Relative St.Dev.	St.Dev.	Relative St.Dev.
Actual	0.1658	1.0000	0.2091	1.0000	0.0684	1.0000
Firm-specific	0.1248	0.7527	0.1382	0.6609	0.0553	0.8085
Macro-sector	0.1035	0.6242	0.2765	1.3223	0.0680	0.9942

Source: author's calculations.

The diagrams show that the standard deviation of the idiosyncratic component commoves with the standard deviation of actual aggregate sales growth, while the macro-sectoral component is much more stable for both all firms and the 100 largest firms. Key finding of Giovanni et al. (2014) is that an idiosyncratic component contributes significantly to aggregate volatility. Russian data show similar results: the standard deviation of firms' idiosyncratic shocks is about 75% of the standard deviation of aggregate sales growth for the entire sample and 80% for the top-100 companies. However, for the Russian economy the contribution of the idiosyncratic component and macro-sectoral component is almost the same for the whole economy. For the 100 largest companies, macro-sectoral shocks are much more for the aggregate sales growth (Friberg R., Sanctuary M, 2016) and Italy (Gnocato N. et al., 2018). This can be explained by the fact that for large firms macroeconomic shocks can have a greater effect due to greater diversification of assets and activities (exchange rate, oil prices, etc.).

Figure 5. Volatility of actual sales growth and its components



Source: author's calculations.

Identification methods used by Giovanni et al. (2014) also allow to estimate the mechanism for firms' contribution to aggregate volatility. Using equation (6), we further decomposed the idiosyncratic component into two terms: the direct channel (variation in individual shocks) and the effect of linkages between firms (covariance of shocks between firms). Figure 6 shows the decomposition of the variation in idiosyncratic component. We can see that the covariance component explains most of firm-specific volatility (Link relative to firm-specific component is about 80%). Similar results were obtained for Italy (Gnocato N. et al., 2018) – about 80%, and for France (Giovanni et al., 2014) – on average 90% is attributable to the linkage component. Foerster et al. (2011) also found that large sectors do not affect the explanation of the volatility of the aggregate industrial production index. Covariance of sectoral growth rates plays an important role.

If we consider the granular component of only the top-100 largest companies, then for such firms the idiosyncratic volatility is due mainly to the variation in individual shocks. The covariance of shocks to these companies is rather small. After 2010, the linkage effect between companies lost its significance. Idiosyncrasy is largely explained by the size of the top-100 firms.

Figure 6. Decomposition of idiosyncratic component on direct effect and linkage effect

Source: author's calculations.

We will examine each of the effects in more detail. We can assume that the fatter are the tails in the distribution of firms by size (i.e. the presence of very large firms), the more concentrated the sectors will be, and the greater the aggregate volatility will be accounted for by idiosyncratic shocks. We will verify this by calculating the direct effect for each sector $DIRECT_{jt} = \sum_{i \in j} w_{i,t-1}^2 Var(\varepsilon_{it})$ and constructing a concentration indicator for the sectors as follows[4]:

[4] The concentration index here is built like the Herfindahl index. However, we cannot interpret it as the Herfindahl index because we use a sample for the analysis, and not the population of firms in the economy.

$$H_{j,t1} = \sum_{i \in j} \left(\frac{Y_{i,t-1}}{Y_{t-1}} \right)^2 \quad (15)$$

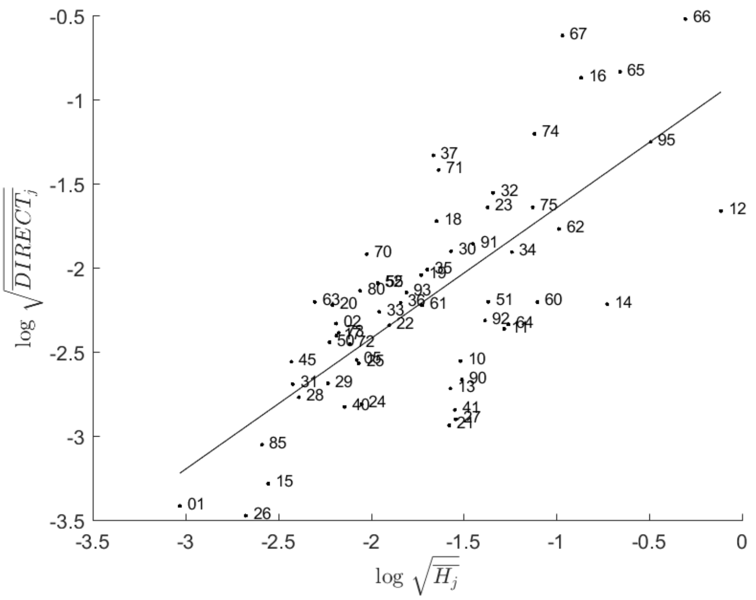
For each sector j by each year, we calculate the concentration index for all firms i in sector j. To build the chart below, we averaged the concentration indices over time, as well as the $DIRECT_{jt}$ variable. Figure 7 shows the average concentration for sectors ($\overline{H}_j$) and the average value of volatility for the same sectors ($\overline{DIRECT_j}$); the numbers on the graph are OKVED codes. The diagram shows that there is a significant positive correlation between these variables, which is in line with the granular hypothesis suggested by Gabaix (2011). Thus, for the Russian economy and for a correct understanding of business cycle dynamics, it is essential to consider idiosyncratic shocks, especially in highly concentrated sectors.

Next, we test the hypothesis about the linkages existing between firms that can also explain the transformation of idiosyncratic shocks into aggregate volatility. One suggestion that can be verified is that companies' outputs are correlated through the input-output system. We will construct an input-output coefficient (*IO coefficient*) similarly to Gnocato N. et al. (2018) and analyse the relationship between this parameter and the value of the $Link$ component from equation (6) for each pair of sectors.

$$\overline{IO}_{rs} = \frac{1}{2}\big((1-\lambda_r)\rho_{rs} + (1-\lambda_s)\rho_{sr}\big) \quad (16)$$

where λ_r is the share of value added in sector r's total output, and ρ_{rs} is the share of inputs sourced domestically from sector s in the sector r's total domestic spending on intermediates, and vice versa. For these calculations, we use data from the Rosstat input-output tables averaged over 2012–2015.

Figure 7. Direct effect and industry concentration index

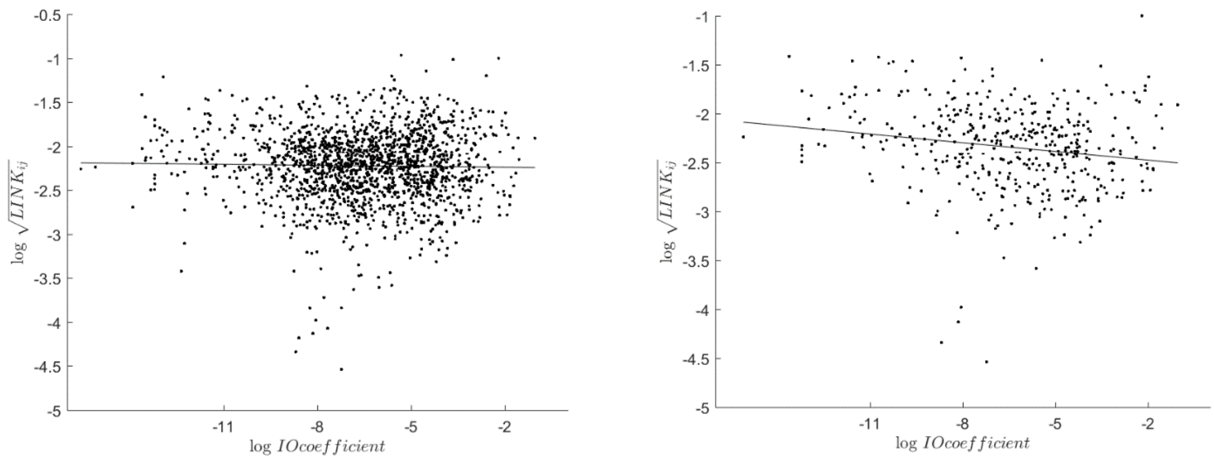


Source: author's calculations.

Figure 8 shows the relationship between cross-sector linkages and average values of the linkage component for the entire economy and for industrial production sectors. The data do not demonstrate any strongly significant relationship, while industrial production companies demonstrate a weak negative correlation (-0.17). The graph presents the logarithmic values of the indicators; consequently, there are no zeros or negative values of covariance in the coefficient of sectoral relations. Negative values in this case mean a substitution effect among competing firms. As for zero values, the proposed hypothesis cannot explain the interaction between industries, where this interaction coefficient is zero.

Figure 8. Covariances of firm-specific shocks across sectors and input-output linkage coefficients

All sectors Manufacturing sectors



Source: author's calculations.

The study of the cross-sector cost structure did not give us a clear answer regarding the nature of linkages between firms. Further analysis is needed. Next, we can assume that linkages between sectors are explained by other factors, for example common shocks in labour market. Gnocato N. et al. (2018) found a positive correlation between the value Link and the regional economic activity concentration index. In this paper, we will also test a similar hypothesis using Rosstat data on the average number of employees for the period of 2009–2016.

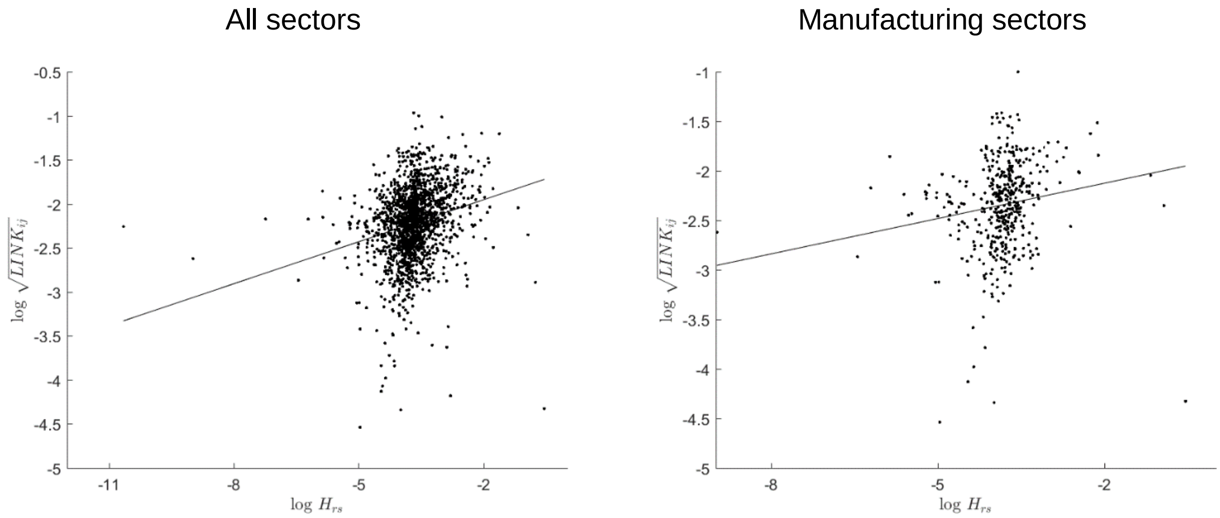
For this analysis, we construct the concentration index of economic activity for the Russian regions as a proxy for measuring cross-sector correlations in the labour market (Gnocato N. et al., 2018):

$$H_{rs} = \sum_{p=1}^{P} z_p^2 = \sum_{p=1}^{P} \frac{\left(\sum_{i \in r \cap p} L_i\right)\left(\sum_{i \in s \cap p} L_i\right)}{\left(\sum_{i \in r} L_i\right)\left(\sum_{i \in s} L_i\right)} \quad (17)$$

where L_i is the number of workers employed by firm i; p is the region's index; r and s index sectors.

Figure 9 shows the correlation between the average of the component $Link$ and the calculated labour market concentration among sectors for the entire economy and for manufacturing sectors. The corresponding values of the correlation coefficient are 0.24 and 0.16.

Figure 9. Covariances of firm-specific shocks across sectors and labour market concentration



Source: author's calculations.

Summing up the results of this section, we can conclude that idiosyncratic shocks have a significant effect on aggregate volatility, mainly through the linkages between companies' shocks. What will be the policy implications if we assume that the Russian economy is characterised by a quite high degree of granularity and the linkages between companies play a significant role in transforming individual shocks into volatility of macro variables? First, the confirmation of the granular hypothesis suggests that estimation of the policy effects one should take into account the presence of firms in the Russian economy affecting volatility of aggregate indicators. In this case, the use of averages or macro variables may not be entirely correct. For instance, even if sectors have almost the same average level of productivity, the firm distribution within sectors may vary significantly due to granularity. Consequently, the same macro policy measures can eventually lead to different consequences, as shown, for example, by Ayyagari et al. (2018). Secondly, granularity means the heterogeneity of firms and the presence of the linkage effect that can create an additional channel for policy to influence the aggregate output and productivity dynamics, and as a result the competitiveness level. It is necessary to understand that if the economy is granular, an inefficient allocation of resources (labour and capital) can cause a slowdown in economic growth and productivity.

4.2 Using information on granularity to build an alternative industrial production index

The above results allow us to identify the idiosyncratic component in macroeconomic series. Using information about the granularity of macroeconomic variables, we can analyse the short-term output dynamics in terms of more stable components and exclude the effects of firm-level shocks or statistical errors. It also helps to understand the nature of this fluctuation: a trend change or a temporary shock to one or a group of firms.

In this paper, we try to recalculate Rosstat industrial production index by re-weighting the sub-indices using information on the effect of idiosyncratic shocks on their volatility. We used the levels of the idiosyncratic component variation calculated for the sectors and relative variation in the total output growth. Next, we ordered the sectors according to the value of the relative variation in the idiosyncratic component. Thus, we obtained new weights that reduce the influence of series that are less resistant to idiosyncratic fluctuations.

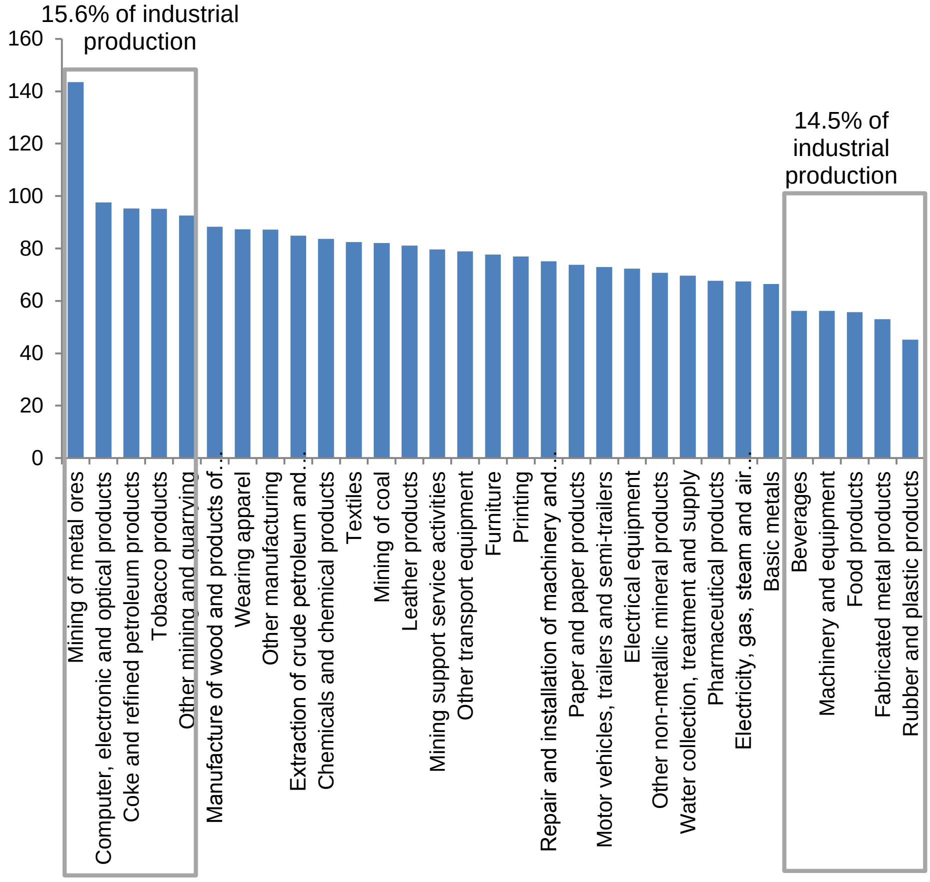
This part of the analysis was prepared using Rosstat data for 30 industrial production sub-indices (Section C ‘Mining’, Section D ‘Manufacturing’, Section E ‘Electric power, gas and water supply') for January 2005–December 2016 (OKVED 2007) and 31 industrial production sub-indices for January 2014–August 2018 according to OKVED 2. The initial weights represent the structure of gross value added in 2010. Below we will consider the series in accordance with OKVED 2 classification. Weights will be calculated as follows:

1) The weights are inversely proportional to the relative variation in the idiosyncratic component on average over the period (Index 1)
2) The weights are inversely proportional to the relative variation in the idiosyncratic component for each year (Index 2)
3) We exclude 50% less stable series according to ranking by relative variation in the idiosyncratic component (Index 3)
4) We exclude 25% less stable series according to ranking by relative variation in the idiosyncratic component (Index 4)
5) For aggregation, we use the most stable components accounting for about 50% of industrial output (Index 5).

Below (Figure 10) are the industrial production sectors in accordance with OKVED 2 classification. More stable sectors in terms of idiosyncratic shocks account for about 14% of total industrial production. The most volatile component in this regard is the metal ore mining series; the variation in the idiosyncratic component is much higher than the variation in actual sales growth for firms in this sector.

Figure 11-13 show the dynamics of the Rosstat industrial production index and a set of indices calculated in accordance with our methodology above. All indices are seasonally adjusted, month over month changes. Volatility indicators show that the indices we have proposed have a lower standard deviation as the corresponding value for a number of indices of industrial production. We see that at certain points over the period, the constructed indices coincide with the actual Rosstat industrial production index, while in other months we can observe significant deviations between the values of these indicators. We can assume that there were no idiosyncratic shocks in the first case, while in other points of time idiosyncratic shocks had a significant impact, and their effect on the industrial production index was smoothed out.

Figure 10. Relative standard deviation of the idiosyncratic component for industrial output series, average value for 2013–2017, %

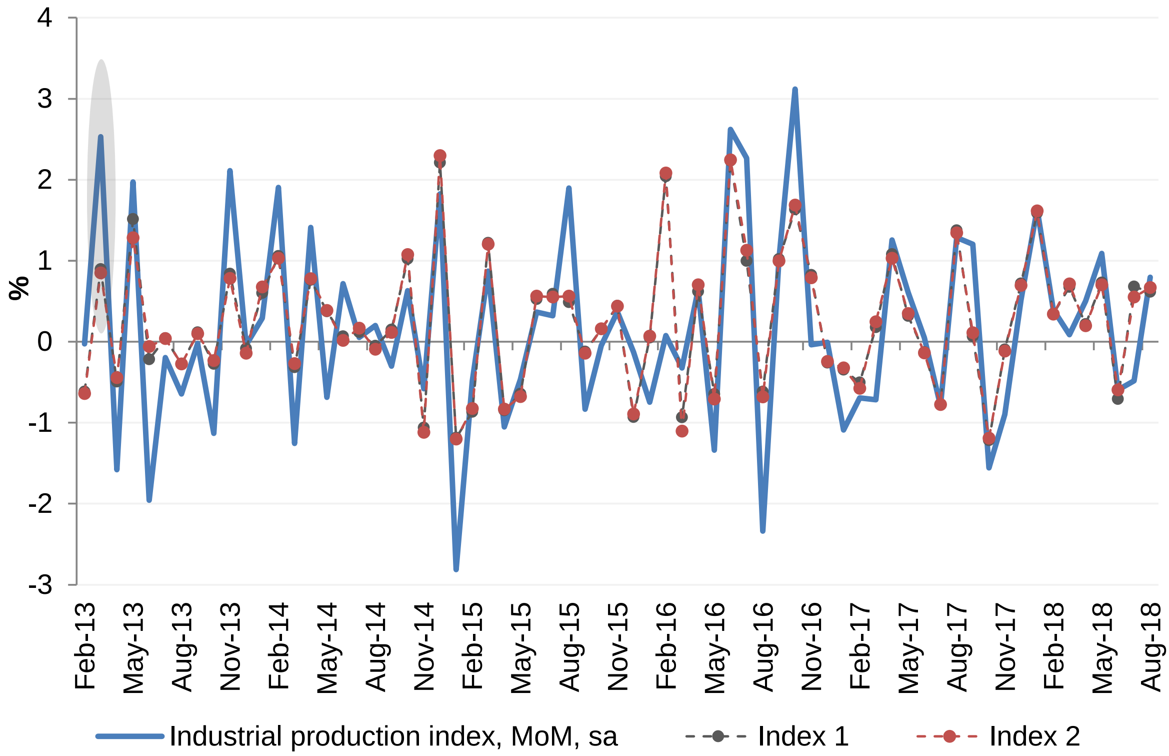


Source: author's calculations.

To illustrate how the index works, we will consider several points in which we notice a significant deviation between the Rosstat industrial production index and the constructed indices: March 2013 (Figure 11), August 2016 (Figure 12) and June 2018 (Figure 13).

In *March 2013*, the seasonally adjusted actual value of the industrial production index increased by 2.53% compared with the previous month. However, Index 1 and Index 2 showed a noticeably lower increase of +0.90% and +0.85%, respectively (Figure 11). During this month, this procedure significantly reduced the positive contributions of sectors such as crude oil and gas production, metal ore mining, and coke and petroleum products, which represent a significant share in gross value added (37.6%). During that month, a number of events took place that affected individual companies operating in these sectors (including large ones). For instance, the purchase by Rosneft of a 100% shares in TNK-BP and the conclusion of this company a loan agreement with China Development Bank to increase oil supplies to China. In contrast, the following large sectors in terms of shares in VAD (food products, basic metals and fabricated metal products, electric power, gas and steam supply accounting for 28%) proved to be most resistant to idiosyncrasy and demonstrated a significant increase in production. The re-weighting increased their positive contribution to the dynamics of industrial production in March 2013.

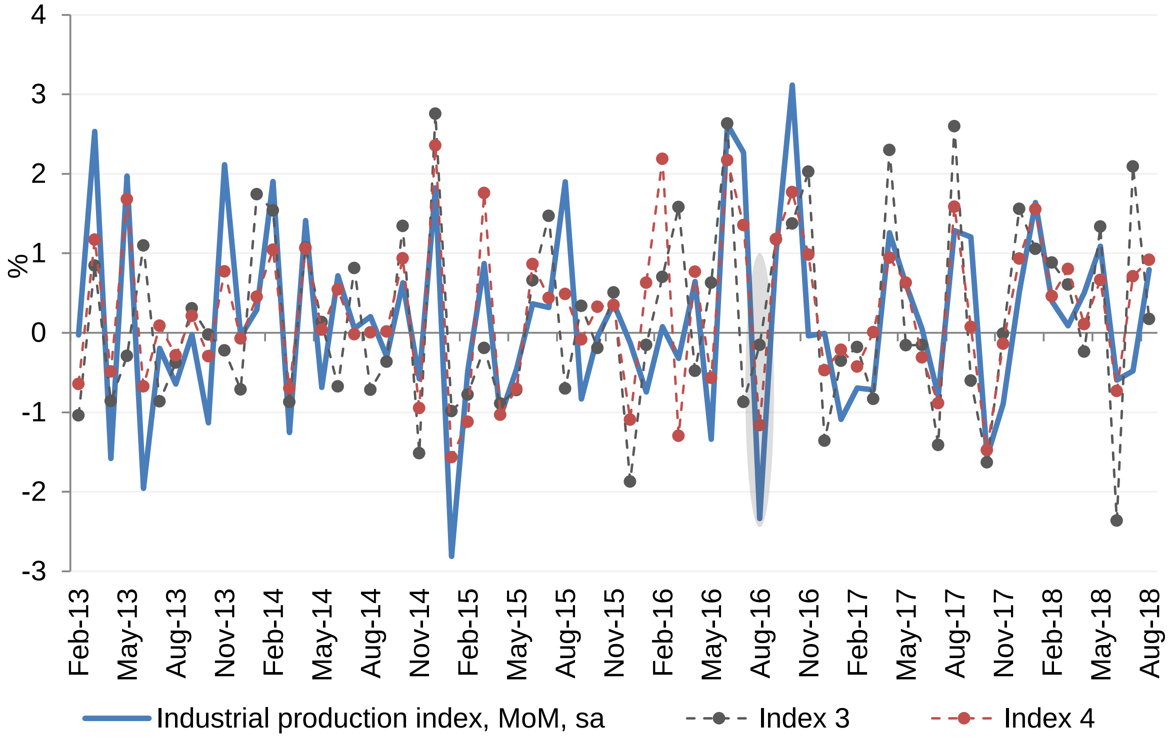
Figure 11. Dynamics of the industrial production index, Index 1 and Index 2



Source: author's calculations.

Seasonally adjusted actual growth of the industrial production index in *August 2016* was -2.3% MoM, while Index 3 and Index 4 did not demonstrate such a dramatic drop: -0.15% and -1.16% MoM, respectively (Figure 12). During this month, the production of other vehicles accounted for the largest negative contribution (taking into account its weight in VAD) to the industrial production dynamics. This sector is rather heterogeneous in terms of its end consumers. It includes production of unique products characterised by significantly different capital intensity and production cycle duration (e.g. production of ships, railway locomotives or aircraft compared to the production of motorcycle and bicycle). The sector is also characterised by one of the largest shares of military production. These facts determine the high volatility observed in the production of other vehicles. In this respect, short-term fluctuations cannot imply any signs of economic downturn or recovery. Index 3 and Index 4 are built by removing the most volatile (50% and 25% of the components, respectively) series in terms of the idiosyncratic component from the aggregate index. According to the model results, the production of other vehicles is included in the 50% of the most volatile components within this definition. Thus, during the month when the production of other vehicles showed the greatest decline, our methodology adjusted the index to exclude the effect of presumably short-term fluctuation in the production of other vehicles.

Figure 12. Dynamics of the industrial production index, Index 3 and Index 4

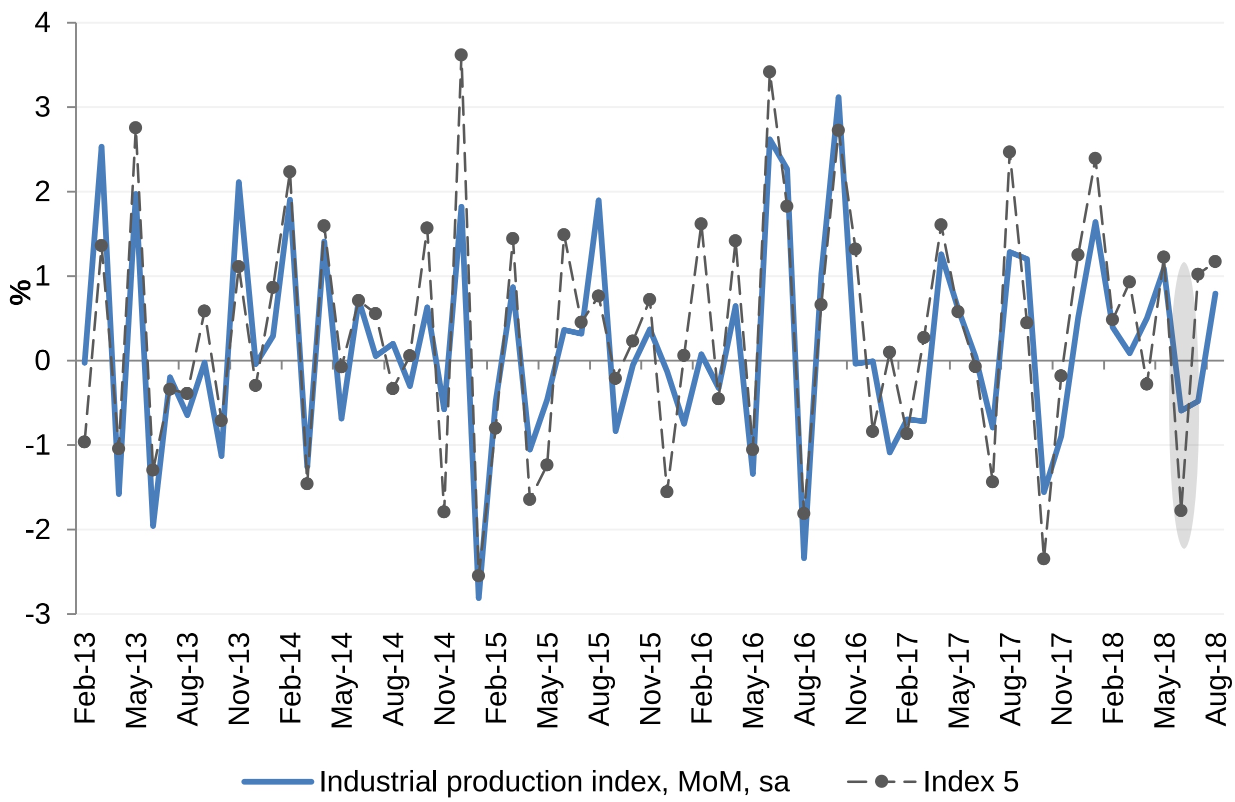


Source: author's calculations.

In June 2018, the industrial production index decreased by 0.59% compared to the previous month (Figure 13) adjusted for seasonal and calendar effects. According to the Research and Forecasting Department, the main reason for this decline in production was a sharp drop in basic metals production due to a decrease in production in sector ‘Production of basic precious metals and other non-ferrous metals, nuclear fuel production’. Index 5 was calculated taking into account data on the production of basic metals as one of the largest and most stable industries for this period. In our sample, the basic metals sector also includes non-ferrous and nuclear metals producers. Thus, in June 2018, the procedure for calculating Index 5 reinforced the negative contribution of the basic metals index. However, we understand what caused this decline. Further, it would probably be reasonable to provide a more detailed breakdown by sector, as we see that this sector includes more heterogeneous production activities.

Thus, this analysis provides more information on industrial production dynamics for a better understanding the reasons behind economic fluctuations. As a result, we can conclude whether we observe a change in production trends in any sector or a temporary shock. In turn, an understanding of the business cycle is essential for assessing the policy efficiency.

Figure 13. Dynamics of the industrial production index and Index 5[5]



Source: author's calculations.

Further, we try to understand what is behind the estimated idiosyncratic shocks. Are they from demand-side or supply side of economy? From a regulatory perspective, it may be important to understand which of these two shocks is dominant. In order to analyse this issue we estimate the industries in terms of their cyclical nature and compare this estimates with the measure of sectors' exposure to idiosyncratic shocks. This procedure helps us to understand how much supply shocks can explain idiosyncratic component. The cyclic measure was evaluated as follows:

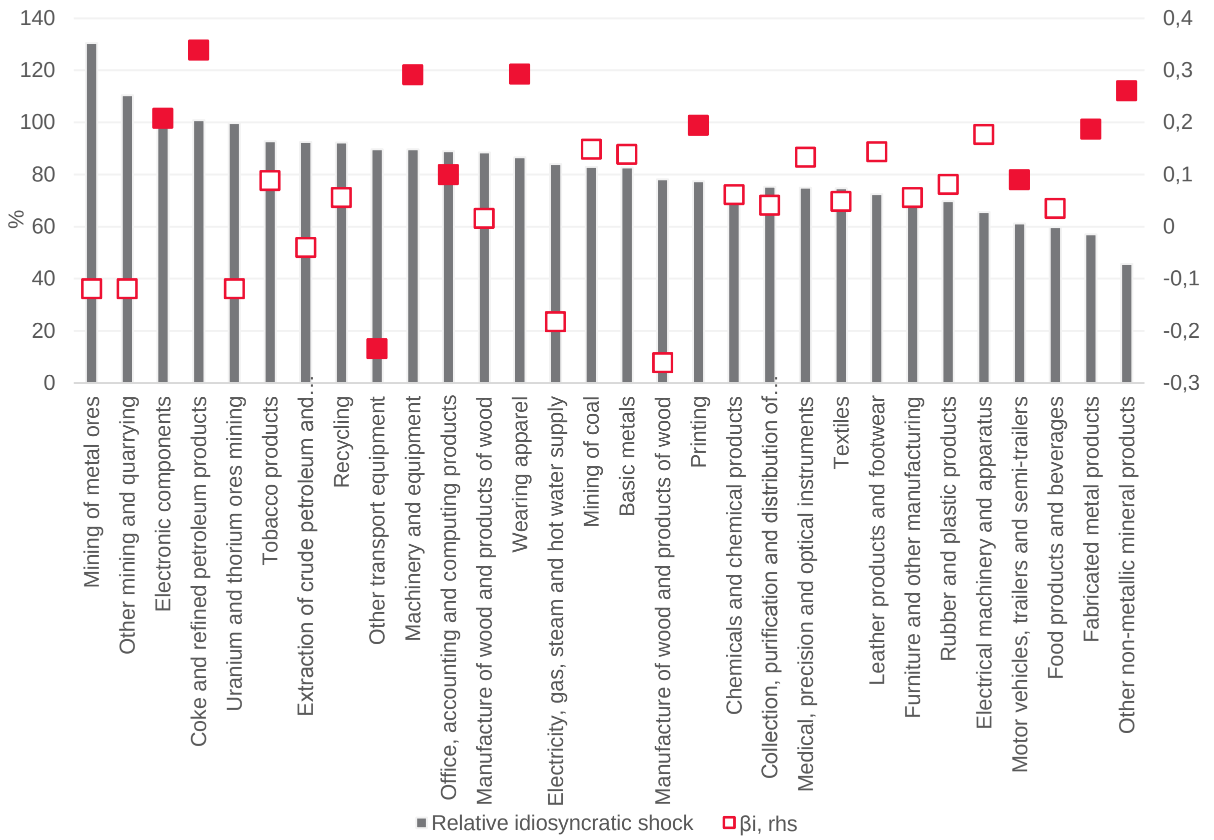
$$\Delta VAD_{it} = \alpha_i + \beta_i \Delta GDP_t + \varepsilon_{it} \quad (18).$$

The coefficient β_i in this equation will reflect the degree of cyclicality of industry i. If the coefficient is significant, the industry will be considered as cyclical. For estimation, we use VAD data for sectors for the period 2004-2017 in accordance with OKVED classification. For the most sectors of Russian economy, the obtained β_i coefficients are statistically insignificant. For instance, for industrial production significance at a 10% level is observed for 10 out of 30 sectors. We should notice that it is

[5] This includes mining services, food and beverages, paper and paper goods, printing production, medicinal products and materials, rubber and plastic products, other non-metal mineral products, metallurgy, finished metal goods, electrical equipment, machinery and equipment, motor transport, trailers and semi-trailers, other vehicles, furniture, machinery and equipment repair and installation, electric power, gas and steam supply, water supply and water disposal, and waste collection and disposal.

difficult to draw a conclusion about the consistency of these estimates, since the assessment was carried out on 14 observations.

Figure 14. Relative standard deviation of idiosyncratic component and the cyclical measure for industrial production, average over 2014-2017



Source: author's calculations.

Figure 14 shows the calculated parameters β_i (red dots are 10% significant) and the values of relative standard deviation of idiosyncratic component for the industry (similar to the values on Figure 10, but new data are built in accordance with OKVED classification). We cannot find any strong connection between these variables. Further, we are planning to develop a more sophisticated method for identifying idiosyncratic shocks, which will allow us to better understand the shocks in terms of supply and demand sides.

5. CONCLUSION

Using microdata on Russian firms' sales over the period of 1999–2017 and using the methodology proposed by Gabaix (2011) and Giovanni et al. (2014), we studied the issue of the granularity in the Russian economy. In particular, we tried to find out whether firm-level shocks affects volatility of macro variables, such as GDP and the industrial production index. According to traditional macroeconomic theory, such shocks are expected to average out at the aggregate level. However, Gabaix (2011) showed that shocks to large firms cannot have a negligible effect, they account for a significant share of macroeconomic volatility. Moreover, firm-level shocks can translate into the aggregate level through linkages between companies (Giovanni et al., 2014).

This research shows that at the micro level, volatility of firms' output is largely due to the idiosyncratic component and not to macroeconomic or sectoral shocks. We also see that the aggregate volatility is mostly accounted for idiosyncratic shocks, while macroeconomic fluctuations are dominant for the 100 largest companies. The estimated idiosyncratic shocks are completely explained by the covariance between companies' shocks, that is, linkages between companies can further spread macroeconomic shocks to individual firms more intensely across business activity in the economy.

For some reasons, confirmation of the granular hypothesis of the Russian economy should probably affect the approach to assessing the policy effects. Firstly, it would not be correct to use average values for analysis, especially during crisis periods when firm-level shocks can have a non-trivial impact on the overall dynamics of business activity. Secondly, because of the granularity, the heterogeneity of firms creates an additional channel of influence on overall production and productivity dynamics, because of which an inefficient allocation of resources will lead to a stronger slowdown in economic growth. The results helped to identify complex structural linkages between companies and the importance of idiosyncratic shocks. Therefore, we must pay more attention to sectoral policies as an essential element of traditional demand policy.

REFERENCES

1. Acemoglu D. et al. The network origins of aggregate fluctuations //Econometrica. – 2012. – V. 80. – No. 5. – P. 1977–2016.
2. Atalay E. How important are sectoral shocks? //American Economic Journal: Macroeconomics. – 2017. – V. 9. – No. 4. – P. 254–80.
3. Ayyagari M., Beck T., Peria M. M. S. M. The Micro Impact of Macroprudential Policies: Firm-Level Evidence. – International Monetary Fund, 2018.
4. Blanco-Arroyo O. et al. On the determination of the granular size of the economy //Economics Letters. – 2018.
5. Castro R., Clementi G. L., Lee Y. Cross sectoral variation in the volatility of plant level idiosyncratic shocks //The Journal of Industrial Economics. – 2015. – V. 63. – No. 1. – P. 1–29.
6. Di Giovanni J., Levchenko A. A., Méjean I. Firms, destinations, and aggregate fluctuations //Econometrica. – 2014. – V. 82. – No. 4. – P. 1303–1340.
7. Di Giovanni J., Levchenko A. A., Mejean I. Large firms and international business cycle comovement //American Economic Review. – 2017. – V. 107. – No. 5. – P. 598–602.
8. Ebeke M. C. H. and Eklou K. M. The Granular Origins of Macroeconomic Fluctuations in Europe. – International Monetary Fund, 2017.
9. Foerster A. T., Sarte P. D. G., Watson M. W. Sectoral versus aggregate shocks: A structural factor analysis of industrial production //Journal of Political Economy. – 2011. – V. 119. – No. 1. – P. 1–38.
10. Fornaro P., Luomaranta H. Aggregate fluctuations and the effect of large corporations: Evidence from Finnish monthly data //Economic Modelling. – 2018. – V. 70. – P. 245–258.
11. Friberg R., Sanctuary M. The contribution of firm-level shocks to aggregate fluctuations: The case of Sweden //Economics Letters. – 2016. – V. 147. – P. 8–11.
12. Gabaix X. The granular origins of aggregate fluctuations //Econometrica. – 2011. – V. 79. – No. 3. – P. 733–772.
13. Gabaix X., Ibragimov R. Rank − 1/2: a simple way to improve the OLS estimation of tail exponents //Journal of Business & Economic Statistics. – 2011. – V. 29. – No. 1. – P. 24–39.
14. Gnocato N. et al. Granular sources of the Italian business cycle. – Bank of Italy, Economic Research and International Relations Area, 2018. – No. 1190.
15. Haltiwanger J. C. Measuring and analysing aggregate fluctuations: the importance of building from microeconomic evidence //Federal Reserve Bank of St. Louis Review. – 1997. – V. 79. – No. 3. – P. 55.
16. Horvath M. Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks //Review of Economic Dynamics. – 1998. – V. 1. – No. 4. – P. 781–808.

17. Karasik L., Leung D., Tomlin B. Firm-specific shocks and aggregate fluctuations. – Bank of Canada Staff Working Paper, 2016. – No. 2016–51.
18. Stella A. Firm dynamics and the origins of aggregate fluctuations //Journal of Economic Dynamics and Control. – 2015. – V. 55. – P. 71–88.

APPENDIX

Table 9. Explanatory power of the granular residuals, model with a dummy variable for 2009

	Dependent variable: real GDP growth rate							
	G1	G1	G2	G2	G3	G3	G4	G4
Γ_t	-0.182 (0.086)	-0.127 (0.077)	-0.148 (0.077)	-0.102 (0.072)	-0.225 (0.143)	-0.346 (0.125)	-0.121 (0.123)	-0.161 (0.131)
Γ_{t-1}		-0.230 (0.106)		-0.236* (0.125)		-0.364 (0.160)		-0.151 (0.226)
i.2009	-0.125*** (0.035)	-0.136*** (0.030)	-0.126*** (0.035)	-0.133*** (0.031)	-0.120*** (0.037)	-0.116*** (0.030)	-0.125*** (0.038)	-0.119*** (0.038)
_cons	0.023 (0.014)	-0.006 (0.017)	0.023 (0.015)	-0.015 (0.024)	0.038*** (0.010)	0.011 (0.013)	0.040*** (0.012)	0.022 (0.024)
N	18	17	18	17	18	17	18	17
R^2	0.553	0.698	0.534	0.650	0.503	0.680	0.455	0.497
R^2_{adj}	0.493	0.628	0.471	0.569	0.436	0.606	0.382	0.381

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*
Source: author's calculations.