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ABSTRACT: This paper provides the first assessment of the contribution of idiosyncratic shocks to aggregate fluctuations in an emerging market using confidential data on the universe of Chilean firms. We find that idiosyncratic shocks account for more than 40 percent of the volatility of aggregate sales. Although quite large, this contribution is smaller than documented in previous studies based on advanced economies, despite a higher degree of market concentration in Chile. We show that this finding is explained by larger firms being less volatile and by weaker propagation effects across Chilean firms.

JEL Classification Numbers:	E32, F41
Keywords:	Business cycle, emerging markets, firm-level shocks, granularity, propagation
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Idiosyncratic Shocks and Aggregate Fluctuations in an Emerging Market*

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Abstract

This paper provides the first assessment of the contribution of idiosyncratic shocks to aggregate fluctuations in an emerging market using confidential data on the universe of Chilean firms. We find that idiosyncratic shocks account for more than 40 percent of the volatility of aggregate sales. Although quite large, this contribution is smaller than documented in previous studies based on advanced economies, despite a higher degree of market concentration in Chile. We show that this finding is explained by larger firms being less volatile and by weaker propagation effects across Chilean firms.

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1 Introduction

Business cycle theory has traditionally assumed that aggregate fluctuations are due to macroeconomic shocks, such as commodity price fluctuations, technological innovations, and macroeconomic policy. Idiosyncratic shocks were instead expected to wash out in the aggregate through a simple diversification argument (Lucas, 1977).

This view has been upended in recent years. Gabaix (2011) showed that if the corporate sector exhibits high levels of market concentration, idiosyncratic shocks to large firms can produce significant aggregate fluctuations. Similarly, Acemoglu et al. (2012) showed that firm idiosyncratic shocks can also generate macroeconomic volatility as they propagate through input-output linkages.[1] Recent analyses using rich firm-level data have provided empirical support for these theoretical predictions. Using data for the universe of French firms, Di Giovanni, Levchenko and Mejean (2014) find that firm idiosyncratic shocks contribute to aggregate fluctuations as much as sectoral and macro shocks. Similarly, Yeh (2017) documents that firm idiosyncratic shocks play an important role in explaining aggregate sale volatility in the United States.

Because of data constraints, the empirical literature on the contribution of idiosyncratic shocks to aggregate fluctuations has been limited to advanced economies. This begs the question of how results may differ in the context of emerging markets. For example, market concentration is often more pronounced in emerging markets. This suggests that idiosyncratic shocks may drive an even larger share of aggregate fluctuations, as hypothesized by Gabaix (2011). On the other hand, emerging markets may be more exposed to foreign macroeconomic shocks because they are generally more open to international trade relative to advanced economies. Emerging markets may also display different network structures that can have a profound impact on the effects of idiosyncratic shocks on aggregate volatility as shown by Acemoglu et al. (2012).

This paper complements the literature by providing the first assessment of the role of idiosyncratic shocks in aggregate fluctuations using firm level data from an emerging market. The analysis uses confidential sales data for the universe of Chilean firms between 2008 and 2019. Sales data are disaggregated by destination markets which allows us to isolate firm idiosyncratic shocks following the approach developed by Di Giovanni, Levchenko and Mejean (2014).

Consistent with the empirical evidence from advanced economics, we find that firm idiosyncratic shocks play a very important role in driving aggregate fluctuations. Specifi-

[1]Other key contributions analyzing the role of idiosyncratic shocks in aggregate fluctuations include Di Giovanni and Levchenko (2012), Carvalho and Gabaix (2013), Atalay (2017), Di Giovanni, Levchenko and Mejean (2018), Baqaee (2018), Baqaee and Farhi (2019), Carvalho and Grassi (2019).

cally, they account for 43 percent of the volatility in total sales. This proportion increases to 52 percent for sales by manufacturing firms. Although very significant, the contribution of idiosyncratic shocks is smaller than found in previous studies based on advanced economies.

To shed light on the reasons underpinning this result, we decompose the contribution of idiosyncratic shocks to aggregate fluctuations into a granular and linkage component. The granular component captures effects of idiosyncratic shocks on aggregate fluctuation arising from the presence of large firms. The linkage component measures instead the extent to which idiosyncratic shocks affect aggregate volatility by spreading to other firms via input-output linkages.

We find that the granular component for Chile is broadly in line with the evidence from advanced economies. This may appear surprising because market concentration is considerably higher in Chile, suggesting a greater potential for large firms to affect aggregate fluctuations. However, the analysis also reveals that large firms in Chile are considerably less volatile that smaller firms. These two effects balance each other out, generating a granular component similar to the one in advanced economies.

The linkage component is instead smaller in Chile than in advanced economies. We document that this is likely because the firm network structure in Chile is more symmetric than in advanced economies. In other words, firms tend to have a more similar number of connections with each other. Therefore, as explained in Acemoglu et al. (2012), idiosyncratic shocks tend to wash out in the aggregate more easily.

The paper is organized as follows. Section 2 describes the data used in the analysis. Section 3 quantifies the contribution of idiosyncratic shocks to aggregate fluctuations. Section 4 decompose the role of idiosyncratic shocks between the granular and linkage components. Section 5 concludes.

2 Data

The analysis uses various sources of confidential administrative firm-level data on the universe of Chilean firms between 2007 and 2019. First, we use the VAT registry from the tax authority to obtain information on total sales at the firm level. Second, we collect information on firms' export sales (free on board) by country destination from the National Customs Service. We compute domestic sales as the difference between total sales and export sales to all destinations. The dataset thus reports firms' sales for a given destination market (foreign country or Chile) that we refer to as firm-destination sales. series We convert sales in Chilean Pesos into real values called *Unidad de Fomento*, a CPI inflation-indexed unit of account calculated and published by the Central Bank of Chile.[2] Lastly, we collect information on the number of employees from the annual statements that firms must file to pay income taxes.

We set some minimum conditions for firms to be in the sample of analysis that mimic those used by Di Giovanni, Levchenko and Mejean (2014). First, given that the analysis focuses on the intensive margin—i.e. on firms that are selling goods to a given market destination every year—we drop discontinued firm-destination sale series over the 2008–2019 sample. Second, we drop firm-destination sale series that display extreme fluctuations, with sales more than doubling in a year or contracting by more than a half. The final sample of analysis includes 40,150 firms and 529,884 firm-destinations, which account for 67.3 percent of the total sales by Chilean firms.

Regarding the quality of the micro level data, we note that firms' sales are tightly correlated with aggregate series. The correlation between firms' aggregate sales and GDP is 83.2 percent. Furthermore, firms' export sales closely mimic export data from the BOP statistics, with a correlation of 93 percent.

Table 1 reports summary statistics illustrating some key features of Chilean firms, distinguishing between the whole economy and the manufacturing sector alone. For comparison purposes, the table also includes statistics for France and the US taken from Di Giovanni, Levchenko and Mejean (2014) and Yeh (2017), respectively. During the sample period, the average growth rate of aggregate sales in Chile was 2.7 percent. This is larger than the unweighted average growth rate of individual firms.[3] Contrary to the results for France, this implies that in Chile smaller firms do not grow more rapidly than larger ones.

The average volatility of firms' sales is almost twice as high as the one in France or the US, with a standard deviation of growth rates equal to about 0.5. As in the case of other countries (especially France), larger firms display lower volatility. We will return to this issue later in the paper because it has important implications for the contribution of idiosyncratic shocks to aggregate fluctuations. Finally, the table reports the Herfindahl indexes at the firm and the firm-destination level. These are considerably higher than for France and the US, reflecting a higher degree of market concentration in Chile.

[2] See https://si3.bcentral.cl/estadisticas/Principal1/metodologias/EC/IND_DIA/ficha_tecnica_UF_EN.pdf.

[3] Note that the table examines the growth rates of sales of a given firm in a given destination. For the sake of simplicity, we talk about firms' growth rates instead of firm-destinations' growth rates.

Table 1: Firms' average growth rates and volatilities

	Chile		France	US
	Whole economy	Manufacturing	Whole economy	Whole economy
Average aggregate growth rate	0.027	0.019	0.037	0.046
Average of individual growth rates	0.012	0.005	0.046	
SD of individual growth rates	0.486	0.513	0.234	0.208
0 - 20 size percentile	0.581	0.576	0.301	0.240
21 - 40 size percentile	0.475	0.505	0.242	0.209
41 - 60 size percentile	0.467	0.511	0.216	0.200
61 - 80 size percentile	0.457	0.491	0.204	0.197
81 - 100 size percentile	0.433	0.473	0.207	0.201
Top 100	0.398	0.366	0.132	
Top 10	0.220	0.156	0.127	
Average $\sqrt{\text{Herf}(f,n)}$	0.057	0.132	0.030	0.034
Average $\sqrt{\text{Herf}(f)}$	0.076	0.141	0.033	0.036

Notes: This table presents the summary statistics for the whole economy and manufacturing firms over 2008–2019. The statistics for France are from Di Giovanni, Levchenko and Mejean (2014) and the statistics for the US are from Yeh (2017). Herf(f,n) is the Herfindahl index of the firm–destination (country) sales shares by year. Herf(f) is the Herfindahl index of the total firm sales shares by year.

3 Idiosyncratic shocks and aggregate fluctuations

As described in the previous section, the Chilean data provide detailed information about firm sales by destination market. This makes it possible to isolate idiosyncratic shocks by removing shocks that are common to the sector and destination market in which the firm operates. Define γ_{fnt} as the growth rate of the sales of firm f to the destination market n at time t. The firm operates in sector j. We decompose γ_{fnt} as follows

$$\gamma_{fnt} = \delta_{jnt} + \varepsilon_{fnt} \tag{1}$$

where δ_{jnt} includes both macro shocks (that impact all firms selling to destination n) and sectoral shocks (that impact all firms operating in sector j and selling to destination n). Therefore, we refer to δ_{jnt} as a macro-sectoral shock. ε_{fnt} captures instead the firm's idiosyncratic shock. Di Giovanni, Levchenko and Mejean (2014) show this decomposition is consistent with models à la Melitz (2003), Eaton, Kortum and Kramarz (2011) and Eaton et al. (2016).

We capture the macro-sectoral shocks δ_{jnt} by averaging the sale growth rates of all firms in sector j selling to the destination market n. The idiosyncratic shocks ε_{fnt} are obtained as the difference between actual sales growth and the macro-sectoral shocks.

Table 2 provides information about the size and volatility of macro-sectoral and idiosyncratic shocks and about their correlation with actual sales. These statistics are computed for total sales (panel A), domestic sales (panel B), and export sales (panel C). In line with the evidence for France and the US, we find that idiosyncratic shocks tend to be more volatile than macro-sectoral shocks, especially in reference to domestic sales. Furthermore, idiosyncratic shocks are much more correlated with actual sales than macro-sectoral shocks. Replicating the analysis for firms in the manufacturing sector delivers similar results.

Table 2: Decomposition of firm sales in macro-sectoral and idiosyncratic shocks

		Whole economy				Manufacturing			
		Obs	Mean	SD	Corr	Obs	Mean	SD	Corr
A. Total sales									
Actual	γ_{fnt}	529,884	0.012	0.486	1.000	106,092	0.005	0.513	1.000
Macro-sectoral	δ_{jnt}	9,264	0.011	0.643	0.266	5,580	0.005	0.573	0.387
Idiosyncratic	ε_{fnt}	529,884	0.000	0.468	0.964	106,092	0.000	0.473	0.922
B. Domestic sales									
Actual	γ_{fnt}	481,044	0.012	0.438	1.000	74,160	0.001	0.362	1.000
Macro-sectoral	δ_{jnt}	504	0.012	0.085	0.137	168	0.004	0.072	0.166
Idiosyncratic	ε_{fnt}	481,044	0.000	0.434	0.991	74,160	0.000	0.357	0.986
C. Export sales									
Actual	γ_{fnt}	48,840	0.017	0.818	1.000	31,932	0.015	0.754	1.000
Macro-sectoral	δ_{jnt}	8,760	0.011	0.661	0.467	5,412	0.005	0.582	0.464
Idiosyncratic	ε_{fnt}	48,840	0.000	0.723	0.884	31,932	0.000	0.668	0.886

Notes: The correlation is computed for each component against the actual.

We now turn to quantify the contributions of macro-sectoral and idiosyncratic shocks to aggregate sale fluctuations. Note that the growth rate of aggregate sales between time $t-1$ and t, γ_{At}, can be expressed as follows:

$$\gamma_{At} = \sum_{j,n} \omega_{jnt-1}\delta_{jnt} + \sum_{f,n} \omega_{fnt-1}\epsilon_{fnt} \tag{2}$$

where ω_{jnt-1} and ω_{fnt-1} are respectively the share of sector j and firm f's sales to destination n in total aggregate sales. The first and second terms on the right-hand side of equation (2) capture fluctuations in aggregate sales due to macro-sectoral and idysioncratic shocks, respectively.

Using equation (2) to decompose the variance of aggregate sales is problematic because of the time variation in the weights. Therefore, following Carvalho and Gabaix (2013) and Di Giovanni, Levchenko and Mejean (2014), we create synthetic growth rates of aggregate sales $\gamma_{At|\tau}$ by keeping the weights constant at the levels prevailing in a given year τ

$$\gamma_{At|\tau} = \sum_{j,n} \omega_{jn\tau-1}\delta_{jnt} + \sum_{f,n} \omega_{fn\tau-1}\epsilon_{fnt} \tag{3}$$

The variance of $\gamma_{At|\tau}$, denoted with $\sigma^2_{A\tau}$, can then be expressed as

$$\sigma^2_{A\tau} = \overbrace{\text{Var}\sum_{j,n} \omega_{jn\tau-1}\delta_{jnt}}^{\sigma^2_{MS\tau}} + \overbrace{\text{Var}\sum_{f,n} \omega_{fn\tau-1}\epsilon_{fnt}}^{\sigma^2_{I\tau}} + \overbrace{\text{Cov}\left(\sum_{j,n} \omega_{jn\tau-1}\delta_{jnt}, \sum_{f,n} \omega_{fn\tau-1}\epsilon_{fnt}\right)}^{COV_\tau} \tag{4}$$

where $\sigma_{MS\tau}$ and $\sigma_{I\tau}$ capture the standard deviation of fluctuations in aggregate sales due to macro-sectoral and idiosyncratic shocks, respectively. COV measures the covariance between aggregate sales fluctuations caused by macro-sectoral and idiosyncratic shocks.

We estimate $\sigma^2_{A\tau}$, $\sigma^2_{MS\tau}$, and $\sigma^2_{I\tau}$ for each $\tau \in [2008, 2019]$ using the corresponding sample variances. Table 3 reports the average value of these estimates computed over τ.[4] We distinguish between the whole economy and the manufacturing sector, as well as between total sales, domestic sales, and export sales. For comparison purposes, the table also reports data for France and the United States as computed by Di Giovanni, Levchenko and Mejean (2014) and Yeh (2017).

As in the case of France and Chile, the analysis confirms that idiosyncratic shocks contribute very significantly to aggregate fluctuations. Idiosyncratic shocks can explain about 43 percent of the aggregate volatility in total sales for the whole economy, as shown by the ratio of the standard deviations σ_I/σ_A. This proportion increases to 52 percent for sales in the manufacturing sector. The contribution of idiosyncratic shocks to aggregate fluctuations is fairly similar across domestic and export sales. The role of idiosyncratic shocks is sizable even if compared to the aggregate volatility generated by macro-sectoral shocks. For example, the ratio $\sigma_I/\sigma_M S$ shows that idiosyncratic shocks can generate as much aggregate volatility as macro-sectoral shocks in the manufacturing sector.

While idiosyncratic shocks play an important role in driving aggregate fluctuations in Chile, their contribution is smaller than in France and the US where idiosyncratic shocks account for 80 and 52 percent of the aggregate volatility in sales for the whole economy. This is somewhat surprising because market concentration in Chile is considerably higher as measured by the Herfindahl index in Table 1. To better understand what explains differences in the contributions of idiosyncratic shocks across countries, the next section examines in more detail the channels through which idiosyncratic shocks affect aggregate

[4] Therefore, $\sigma^2_A = \sum_\tau \sigma^2_{A\tau}/T$, $\sigma^2_{MS} = \sum_\tau \sigma^2_{MS\tau}/T$, and $\sigma^2_I = \sum_\tau \sigma^2_{I\tau}/T$ where T is the number of τ observations.

Table 3: Contributions of macro-sectoral and idiosyncratic shocks to aggregate volatility

		Chile		France	US
SD of:		Whole economy	Manufacturing	Whole economy	Whole economy
		A. Total sales			
Actual	σ_A	0.082	0.087	0.021	0.035
Macro-sectoral	σ_{MS}	0.058	0.055	0.011	0.023
Idiosyncratic	σ_I	0.036	0.046	0.017	0.018
	σ_I/σ_A	0.434	0.522	0.801	0.520
	σ_I/σ_{MS}	0.609	0.826	1.514	0.780
		B. Domestic sales			
Actual	σ_A	0.076	0.079	0.020	
Macro-sectoral	σ_{MS}	0.053	0.049	0.011	
Idiosyncratic	σ_I	0.037	0.049	0.015	
	σ_I/σ_A	0.489	0.621	0.786	
	σ_I/σ_{MS}	0.700	1.004	1.375	
		C. Export sales			
Actual	σ_A	0.135	0.148	0.036	
Macro-sectoral	σ_{MS}	0.129	0.104	0.013	
Idiosyncratic	σ_I	0.070	0.066	0.030	
	σ_I/σ_A	0.514	0.446	0.842	
	σ_I/σ_{MS}	0.538	0.636	2.357	

Notes: The table reports the averages of each component over the period $1/T\sum_{\tau=2008}^{2019}$.

dynamics.

4 Disentangling the role of granularity and firm linkages

Following Carvalho and Gabaix (2013), we decompose the contribution of idiosyncratic shocks to aggregate fluctuations, $\sigma^2_{I\tau}$, as follows

$$\sigma^2_{I\tau} = \overbrace{\sum_{f,n} w^2_{fn\tau-1}\,\mathrm{Var}(\varepsilon_{fnt})}^{\sigma^2_{G\tau}} + \overbrace{\sum_{g\neq f, m\neq n}\sum_{f,n} w_{gm\tau-1} w_{fn\tau-1}\,\mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt})}^{\sigma^2_{L\tau}} \tag{5}$$

The term $\sigma^2_{G\tau}$ captures the contribution of firms' idiosyncratic shocks to aggregate fluctuations, absent propagation mechanisms across firms. When firm sizes are drawn from a distribution with finite variance, this term rapidly goes to zero as the number of firms increases. This diversification argument underpins the traditional assumption that idiosyncratic shocks do not matter for aggregate fluctuations. However, Gabaix (2011) showed that if the firm size distribution is fat-tailed—i.e. the economy is granular—the contribution of idiosyncratic shocks to aggregate fluctuations decays at a much slower rate. In this context, shocks to large firms can have sizeable effects on aggregate volatility and the term $\sigma^2_{G\tau}$ measures the variance of Gabaix (2011)'s granular residual. The granular residual also depends on how firm volatility varies with firm size, as discussed in detail by Yeh (2017). Specifically, the granular component is smaller if larger firms display a lower volatility of smaller firms.

The term $\sigma^2_{L\tau}$ captures instead the contribution to aggregate volatility arising from firm linkages measured via the covariances between idiosyncratic shocks to different firms. As shown in Foerster, Sarte and Watson (2011), Gabaix (2011), and Acemoglu et al. (2012), these covariances can be driven by input-output linkages. For example, a negative productivity shock faced by a supplier can propagate to downstream firms through an increase in input costs. Or a negative shock to a downstream firm can hurt suppliers by reducing the demand for intermediate inputs. These propagation mechanisms can lead to aggregate fluctuations if the network structure is asymmetric, for example if a few firms sell inputs to a large number of other firms. In this case, shocks to the few upstream suppliers can have cascading effects on a large number of downstream firms.

Table 4 reports the contributions of the granular and linkage components to aggregate fluctuations. The granular component accounts for about one fifth of the aggregate sales volatility. This is a sizeable contribution, similar to the one for France and larger than the one for the US, where the granular component accounts for 21 and 15 percent of aggregate fluctuations, respectively.

Table 4: Contributions of granularity and firm linkages in aggregate fluctuations

		Chile		France	US
SD of:		Whole economy	Manufacturing	Whole economy	Whole economy
Actual	σ_A	0.082	0.087	0.021	0.035
Granular	σ_G	0.017	0.029	0.004	0.005
Link	σ_L	0.031	0.035	0.015	0.017
	σ_G/σ_A	0.203	0.336	0.208	0.149
	σ_L/σ_A	0.381	0.397	0.721	0.489

Notes: The table reports the averages of each component over the period $1/T \sum_{\tau=2008}^{2019}$.

As previously discussed, the granular component is affected by the degree of market concentration and by the relation between firm size and volatility. To illustrate the importance of these two factors, we recompute the granular component under two alternative assumptions. First, we impose that all firms have equal size.[5] In this case, the standard deviation of the granular component, σ_G, drops to only 0.0022. This is about 7 times

[5] For a given τ and assuming that all firms have equal size, the variance of aggregate sales due to granular component is equal to $\text{Var}(\varepsilon_{fnt})/N_{\tau-1}$.

smaller than the standard deviation of the granular component that accounts for differences in firm size, $\sigma_G = 0.0166$, highlighting the importance of market concentration.

Second, we compute the granular component assuming that all firms have the same variance, equal to the average level in the data. Table 1 already provided an indication that larger firms tend to be less volatile. To further document this finding, we estimate the following regression:

$$\ln \sigma_{ft} = \alpha \ln size_{ft} + \lambda_f + \eta_j + v_t + \varepsilon_{ft} \tag{6}$$

where σ_{ft} is the average volatility of firm f during a four-year (non-overlapping) period indexed with t; $size_{ft}$ is the average size of firm f measured using firm sales or employment; λ_f, η_j, and v_t denote firm, sector, and period fixed effects, respectively; and ε_{ft} is the error term.[6] The regression results show a highly statistical negative association between firm volatility and size which tends to reduce the importance of the granular component.[7] Indeed, if all firms had the same variance, the standard deviation of the granular component, σ_G, would increase to 0.0276 which is almost twice as large as the baseline value.

While the granular component in Chile is in line with or slightly larger than the one in France and the US, the contribution of firm linkages to aggregate volatility is considerably lower in Chile. Table 4 shows that the link component accounts for about 38 percent of aggregate fluctuations in Chile while it explains 72 and 49 percent of aggregate volatility in France and the US, respectively.

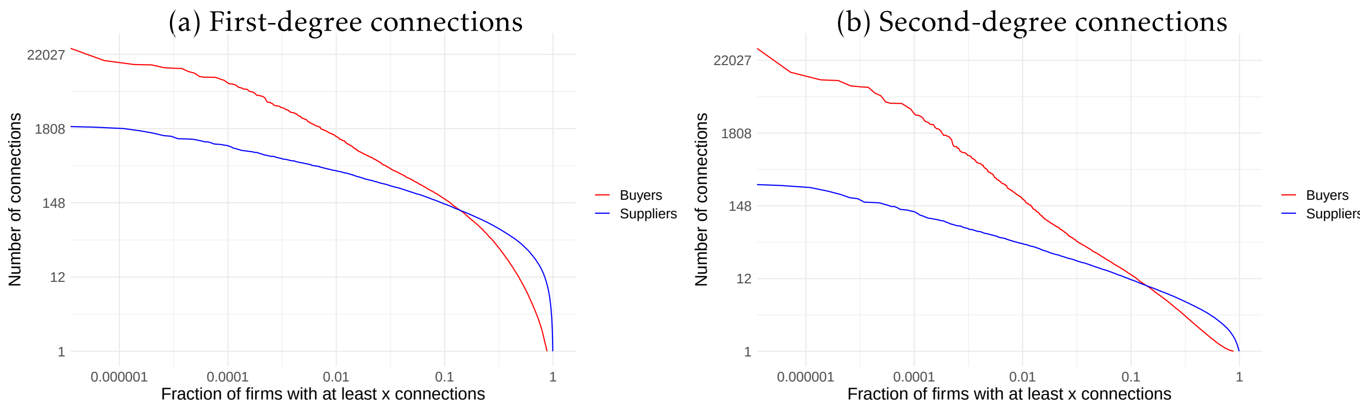
As previously discussed, the contribution of firm linkages to aggregate fluctuations depends on asymmetries in the production network. Following Acemoglu et al. (2012), we illustrate this aspect by examining the distribution of firms' in and out-degrees. Figure 1 shows that first and second-degrees both vis-à-vis suppliers and buyers follow a highly skewed distribution, with a few firms having a disproportionate number of connections. These distributions are well approximated with a Pareto function. The estimated parameters of the Pareto distribution for the first-degree connections with suppliers and buyers are -0.28 and -0.40, respectively. These values are in line with those estimated for other emerging markets. For example, Cardoza et al. (2020) analyze firm level data from the Dominican Republic and find that first-degree connections with suppliers and

[6] The specification is similar to the one estimated in Koren and Tenreyro (2013) and Yeh (2017), even though our data cover a shorter period. As shown by Stanley et al. (1996), this specification can be derived by assuming a power law relationship between firm-level volatility and size, where the rate at which firm-level volatility falls in size is constant.

[7] The results are available upon request to the authors.

buyers follow Pareto distributions with coefficients equal to -0.30 and -0.43, respectively. Alfaro-Urena et al. (2018) examine the domestic production network in Costa Rica and find Pareto coefficients equal to -0.58 and -0.73 for first-degree connections with buyers and sellers, respectively.

Figure 1: Share of firms and number of connections, 2019



Notes: The parameters estimated for the Pareto distributions of per-firm first-degree suppliers and per-firm first-degree buyers are -0.28 and -0.40, respectively; the parameters for per-firm second-degree suppliers and per-firm second-degree buyers are -0.10 and -0.07.

However, network asymmetries appear to be even larger in advanced economies. For example, Bernard, Moxnes and Saito (2019) find that first-degree connections with buyers and sellers in Japan follow a Pareto distribution considerably more skewed than in Chile, with coefficients equal to -1.50 and -1.32, respectively. This could explain why the contribution of firm linkages to aggregate volatility in Chile is not as high as documented for other advanced economies, such as France and the United States.

5 Conclusions

In this paper, we have provided the first assessment in the literature about the contribution of idiosyncratic shocks to aggregate fluctuations in an emerging market economy. Using detailed information on sales of the universe of Chilean firms differentiated by sector and destination market, the analysis has shown the idiosyncratic shocks play an important role in driving aggregate fluctuations. Specifically, idiosyncratic shocks can explain about 43 percent of the aggregate volatility in total sales.

Yet, the contribution of idiosyncratic shocks to aggregate fluctuations is smaller than in advanced economies, namely in France and the US where similar analyses have been performed. This is the end result of three forces at play. On the one hand, market concentration is higher in Chile. This amplifies the role of idiosyncratic shocks because shocks to large firms exercise a disproportionate impact on aggregate volatility. On the other hand, the analysis has shown that in Chile large firms tend to be considerably less volatile than smaller firms. This reduces the effects of large firms on aggregate volatility. These two factors—higher market concentration and negative correlation between firm size and volatility—broadly offset each other from a quantitative standpoint.

The lower contribution of idiosyncratic shocks to aggregate fluctuations in Chile should thus be traced back to a third factor. The network structure of firms' connections in Chile appears to be more symmetric—with firms having similar number of connections with other firms—than in more advanced economies. This implies that idiosyncratic shocks are less likely to generate asymmetric effects through input-output linkages that would give rise to aggregate fluctuations.

The analysis presented in the paper suggests fruitful areas for future research. First, the fact that idiosyncratic shocks generate considerable aggregate volatility even in emerging markets underscores the importance to better understand and more closely monitor individual firm dynamics and linkages. Second, as firm-to-firm transaction data become available for more countries, it would be interesting to investigate more systemically if there are differences in the firms' network structures between emerging and advanced economies and uncover the underlying determinants.

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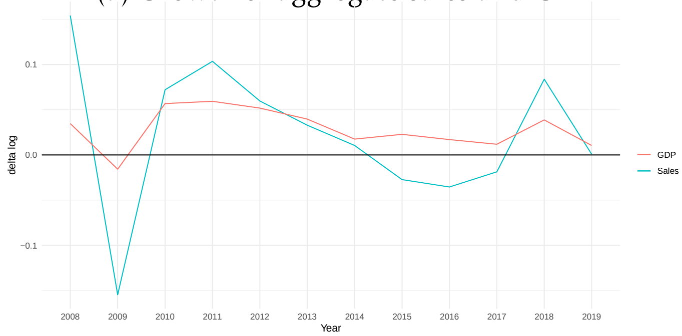
Appendix

A Correlation between micro and macro data

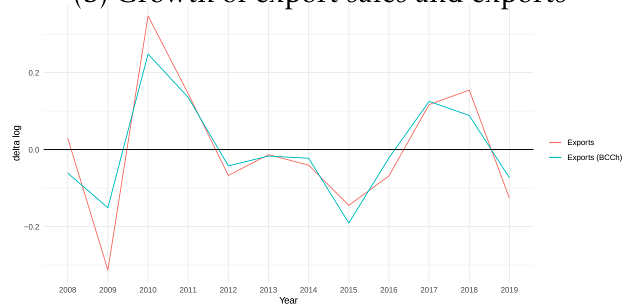
Panel A.1a of Figure A.1 displays the growth rate of aggregates sales (domestic and export sales) of the 40,150 firms in the sample—which represent 67.3 percent of sales of the universe of Chilean firms—and GDP growth. The sales series tracks well the GDP one with a correlation of 83.2 percent, confirming that our sample of firms picks up relatively well the cycle of the economy. Similarly, panel A.1b shows the growth rate of the firm-level export data from the customs authorities along with the growth rate of the exports data from the balance of payments data.[8] The correlation in this case is 93 percent.

Figure A.1: Correlation of firm-level data with macro aggregates

(a) Growth of aggregate sales and GDP



(b) Growth of export sales and exports



Notes: Panel (a) shows the growth rate of the sum of firms' sales and the growth rate of GDP; the correlation is 83.2 percent. Panel (b) shows the growth rate of the sum of firms' export sales and the growth rate of exports from the national accounts; the correlation is 93.0 percent.

B Firms' size and volatility

Figure B.1 provides a graphical representation of some key facts about the Chilean economy. Panel B.1a shows the probability plot of the log of firms' sales, which is used as a proxy for the size of the firms. If the size of the firms was normally distributed, we would expect the dots to be aligned to the red line. Instead, the evidence shows that firms on the right tail of the distribution are larger than implied by a normal distribution.[9] At the

[8] The customs data provide the free on board value of each firm's exports to each of the foreign destinations.

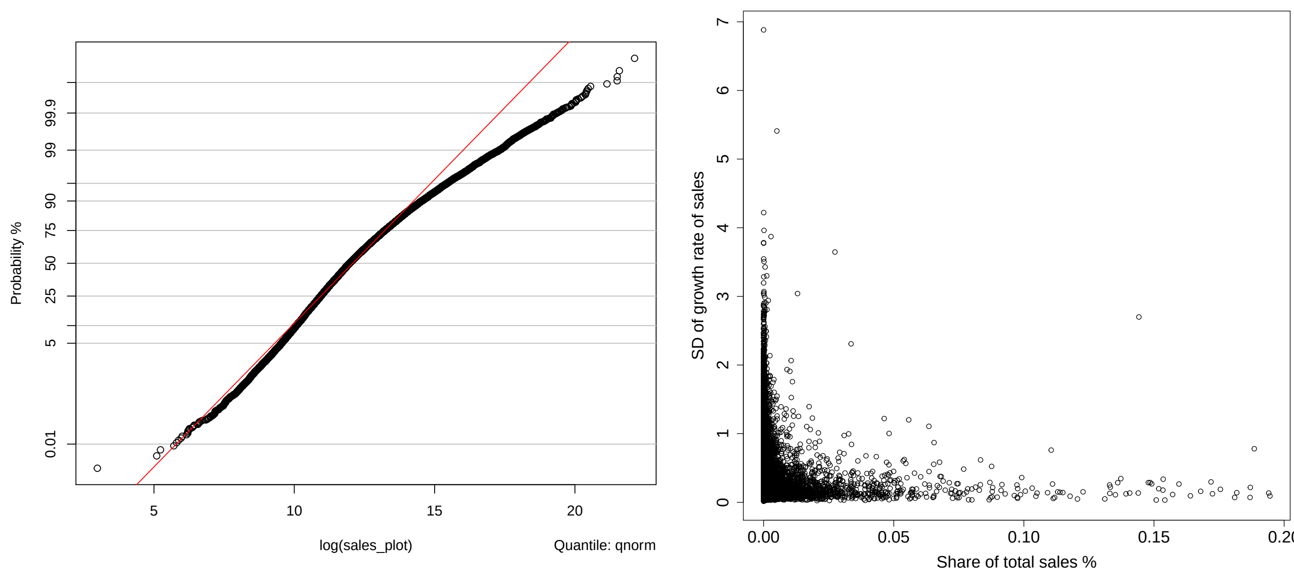
[9] The Anderson-Darling test rejects the hypothesis that the data follows a normal distribution.

same time, panel B.1b shows that larger firms—those with a larger share of total sales—observe a less volatile growth rate of sales, which is in line with the results reported in Table 1.[10]

Figure B.1: Firms' size and volatility

(a) Fat-tailed firm size distribution

(b) Firm volatility-size relationship



Notes: Panel (a) shows the probability plot of individual firms' log sales. Panel (b) shows the relationship between firms' size (measured as a share of sales) and volatility (measured as the standard deviation of the growth rate of sales); to ease visualization, the maximum of the horizontal axis is set to 0.2 percent of total sales.

We confirm the existence of a negative relationship between firm size and volatility by estimating the log-linear form of the power law relationship between the the standard deviation of sales growth and firm sales. Columns (1) to (4) of Table B.1 report the results from different specifications, from the unconditional relationship in column (1), to a specification that controls for firm fixed effects in column (2), for sector fixed effects in column (3), and both firm and sector fixed effects in column (4). As a robustness exercise, we estimate the same specifications in columns (5) to (9) replacing sales with employment. The results point to an unambiguous violation of the Gibrat's law. Our preferred specification is in column (4), as it uses sales as a measure of size (consistent with the rest of the analysis) and includes both firm and sector fixed effects, so that the coefficient is identified using within-firm variation.

Another way of showing the same result is to plot separately the two factors that

[10]The messages are consistent if we use the employment rather than sales to proxy firms' size.

Table B.1: Estimation of the power law between firm size and variance

	Ln SD of sales growth				Ln SD of employment growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln sales	-0.039***	-0.174***	-0.041***	-0.174***				
	(0.007)	(0.015)	(0.005)	(0.018)				
Ln employment					-0.032***	-0.162***	-0.035***	-0.162***
					(0.003)	(0.009)	(0.003)	(0.011)
Firm fixed effects		✓		✓		✓		✓
Sector fixed effects			✓	✓			✓	✓
Observations	120,450	120,450	120,450	120,450	120,450	120,450	120,450	120,450
R^2	0.047	0.642	0.147	0.642	0.032	0.529	0.058	0.529

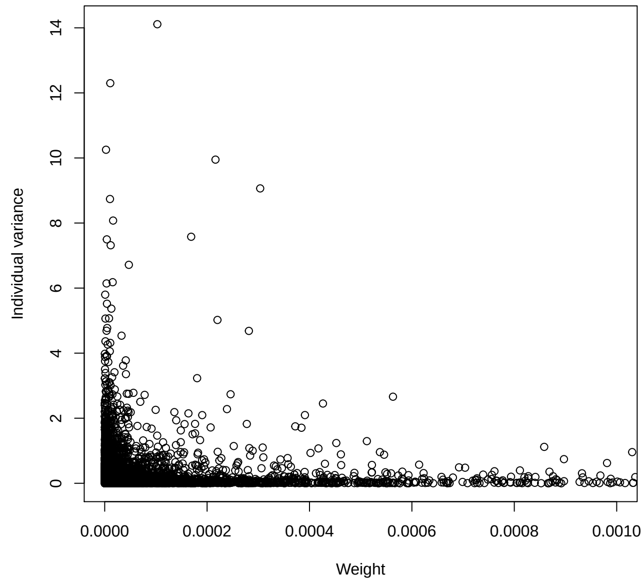
Notes: The regressions are run on four-year non-overlapping periods. All regressions include time fixed effects. Columns (1) and (5) include a constant. Clustered standard errors at the industry level in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

enter the calculation of the granular component in equation (5), that is the variances at the firm-destination level against their weights. Figure B.2 confirms the existence of the negative relationship.

C Firm-specific volatility: a decomposition

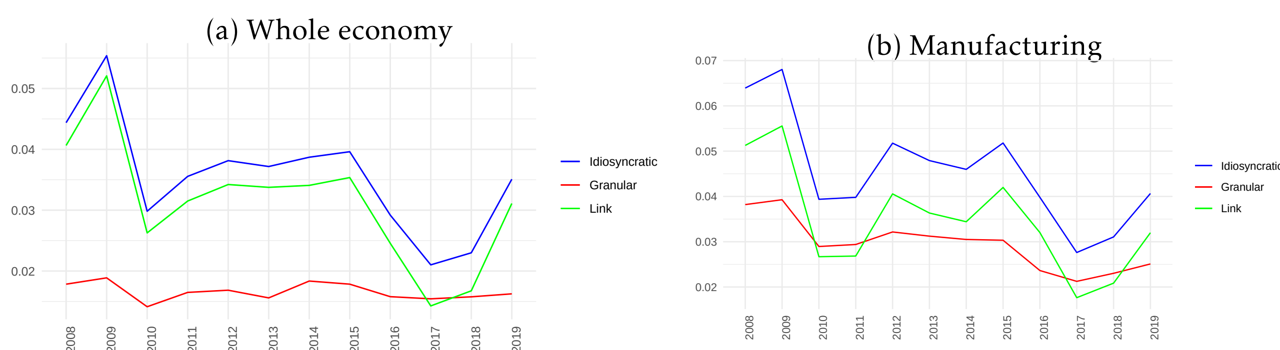
Figure C.1 shows the decomposition of idiosyncratic shocks—or firm-specific volatility—into the granular and link components over τ as defined in equation (5). Both for the whole economy (panel C.1a) and the manufacturing sector (panel C.1b), the contribution of the link component is generally larger than the contribution of granular component, even though it is significantly smaller than for France or the US. The link component is also the one that varies the most over time, effectively driving the fluctuations in the idiosyncratic shocks.

Figure B.2: Volatility and size



Notes: This figure presents firm-destination variances and weights.

Figure C.1: Decomposition of firm-specific volatility



Notes: This figure presents the contribution of firm-specific variances and cross-firm covariances to firm-specific fluctuations.