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MURILO ROCHA E SILVA

A GRANULAR PERSPECTIVE ON THE BRAZILIAN BUSINESS CYCLES: EVIDENCE FROM THE IMPACT OF LARGE FIRMS

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A GRANULAR PERSPECTIVE ON THE BRAZILIAN BUSINESS CYCLES: EVIDENCE FROM THE IMPACT OF LARGE FIRMS

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A granular perspective on the Brazilian business cycles: evidence from the impact of large firms

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RESUMO

Esta dissertação de mestrado investiga se a hipótese granular proposta por Gabaix (2011) aplica-se à economia brasileira. Conjectura-se que dado que as economias modernas são compostas por grandes empresas, uma parte substancial das flutuações agregadas surge de choques idiossincráticos a elas, em vez de choques difusos que afetam diretamente todas as firmas. Examina-se dados trimestrais e anuais ao nível das empresas para estudar as origens microeconômicas dos movimentos agregados. Empregando regressões de mínimos quadrados, encontra-se que choques idiossincráticos às 100 maiores companhias explicam cerca de um terço das flutuações do crescimento do PIB. Adicionalmente, a volatilidade granular é calculada, a qual é a volatilidade que surge de choques ao nível das firmas, e compara-se com a volatilidade agregada. Além disso, o tamanho granular da economia brasileira é computada, atingindo o número de 130 firmas granulares.

Palavras-chave: Teoria dos ciclos de negócios; Granularidade; Choques idiossincráticos; Firmas brasileiras; Flutuações agregadas.

RESUMO EXPANDIDO

Introdução

Há uma literatura importante na última década estudando a origem das flutuações agregadas decorrentes de choques microeconômicos. Um dos métodos se concentra em mostrar que, quando a distribuição de tamanho das empresas possui caudas grossas, o teorema do limite central não se sustenta e, portanto, choques idiossincráticos não se anulam no agregado (GABAIX, 2011). Outro foco é a presença de ligações intersetoriais assimétricas, levando a uma volatilidade agregada considerável advinda de choques setoriais idiossincráticos (ACEMOGLU et al., 2012).

Pesquisas anteriores se concentraram no uso de choques agregados para explicar os ciclos de negócios, argumentando que os choques individuais de empresas se cancelam se houver um grande número de empresas *N*, pois choques positivos para algumas empresas são compensados por choques negativos em outras. A hipótese granular proposta por Gabaix (2011) desafia essa visão e sua abordagem de firma representativa, a qual implica a existência de um certo nível de homogeneidade entre as empresas que operam no mercado.

A hipótese granular oferece uma microfundamentação para os choques agregados de modelos reais de ciclo de negócios, no sentido de que os choques não são mais misteriosos choques agregados de produtividade. Em vez disso, são choques bem definidos em empresas individuais. A hipótese granular pode nos aproximar de uma compreensão concreta da composição microeconômica do PIB e das flutuações ao nível das empresa (GABAIX, 2011). Pode ser uma resposta sólida à pergunta de Cochrane (1994): "quais são os choques que impulsionam as flutuações econômicas?".

Essa hipótese granular pode apontar novos caminhos para a pesquisa macroeconômica no Brasil, em particular que questões macroeconômicas podem ser elucidadas considerando o comportamento de grandes empresas. Por exemplo, ponderar sobre choques ao nível das empresas pode resultar numa melhora da percepção das flutuações do PIB, pois o resíduo granular e a volatilidade granular podem complementar os preditores de PIB existentes.

Objetivos

O objetivo principal desta dissertação é quantificar o impacto de choques idiossincráticos das maiores empresas brasileiras nas flutuações do PIB. Isso já foi medido na Europa (EBEKE; EKLOU, 2017), Espanha (ARROYO; ALFARANO, 2017; BLANCO-ARROYO et al., 2018), Finlândia (FORNARO; LUOMARANTA, 2018) e Austrália (MIRANDA-PINTO; SHEN , 2019), por exemplo.

Para alcançar isso, utilizamos dados de receita das maiores empresas não financeiras do Brasil (provenientes da revista Exame e da Economatica) a fim de investigar se a hipótese granular se aplica à economia brasileira. Posteriormente, calculamos o resíduo granular das 100 maiores empresas e regredimos contra o crescimento do PIB. Além disso, comparamos a volatilidade granular com a volatilidade agregada para verificar se há a presença de um sistema de alerta prévio em funcionamento na economia brasileira. Também estimamos o tamanho granular da economia brasileira considerando o trabalho de Blanco-Arroyo et al. (2018), porque até então a questão de quantas empresas granulares existem em uma economia havia sido deixada sem resposta.

Metodologia

A metodologia empregada nesta dissertação consiste no cálculo de dois indicadores para investigar a hipótese granular: 1) o "resíduo granular" é uma medida parcimoniosa dos choques para as maiores empresas da economia (GABAIX, 2011); e 2) a "volatilidade granular" é um construto que pode ser usado como um sistema de alerta prévio da volatilidade do PIB (CARVALHO; GABAIX, 2013). Um modelo de regressão linear também é empregado com o propósito de quantificar o impacto do resíduo granular nas flutuações agregadas. Os modelos utilizados possuem forte base empírica e robustez teórica.

Resultados e discussão

Esta pesquisa sugere que grandes empresas podem oferecer uma perspectiva útil sobre o ciclo de negócios brasileiro. Os resultados mostram que choques idiossincráticos das 100 maiores empresas brasileiras explicam uma grande parte das flutuações do PIB (um terço, dependendo da especificação). Embora movimentos agregados, como mudanças nas políticas monetária, fiscal e cambial, sejam claramente fatores importantes da atividade macroeconômica, eles não são os únicos contribuintes para os ciclos agregados.

Além disso, a volatilidade granular pode servir como um sistema de alerta precoce para rastrear a volatilidade futura do PIB. Portanto, acompanhar o desempenho das principais empresas é crucial para entender as flutuações agregadas. Usando a metodologia de Blanco-Arroyo et al. (2018), identificamos que aproximadamente 130 empresas granulares desempenham um papel de destaque.

Curiosamente, a Grande Recessão de 2008 marca uma forte ruptura no fenômeno da granularidade ao considerar dados trimestrais, com os R^2s despencando para níveis muito baixos no período 2009-2018. O colapso da hipótese granular após o final da Grande Recessão é, por si só, uma descoberta interessante e intrigante.

Considerações finais

Nossos resultados estão alinhados com as contribuições empíricas da literatura internacional e contribuem para fortalecer a relevância da hipótese granular. A economia brasileira, como a economia dos EUA, é povoada por um grande número de pequenas e médias empresas cuja evolução individual não tem impacto significativo no nível agregado. Enquanto choques de um pequeno número de grandes empresas contribuem significativamente para o ciclo de negócios brasileiro.

A importância dos choques idiossincráticos na volatilidade agregada leva a várias implicações. Para entender melhor as origens das flutuações macroeconômicas, não se deve concentrar exclusivamente em choques agregados, mas em choques concretos de grandes firmas, como Petrobras, Vale ou Ambev. Os resultados desta pesquisa destacam a importância de desviar da estrutura de firma representativa e, em vez disso, considerar a heterogeneidade no nível das empresas na modelagem do ciclo de negócios brasileiro.

Palavras-chave: Teoria dos ciclos de negócios; Granularidade; Choques idiossincráticos; Firmas brasileiras; Flutuações agregadas.

ABSTRACT

We investigate whether the granular hypothesis proposed by Gabaix (2011) holds for the Brazilian economy. We conjecture that because modern economies are made up of large companies, a substantial part of the aggregate fluctuations arise from their idiosyncratic shocks, rather than from diffuse shocks directly affecting all firms. We examine quarterly and annual firm-level data to study the microeconomic origins of aggregate movements. Employing least squares regressions, we find that idiosyncratic shocks to the top 100 companies explain around a third of GDP growth fluctuations. We also compute the granular volatility, which is the volatility that arises from firm-level shocks, and compare it with aggregate volatility. Moreover, we calculate the granular size of the Brazilian economy, reaching the number of 130 granular firms.

Keywords: Business cycle theory; Granularity; Idiosyncratic shocks; Brazilian firms; Aggregate movements.

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1 INTRODUCTION

There has been a growing body of research over the last decade studying the origin of aggregate fluctuations arising from microeconomic shocks. One of the methods focuses on showing that when firm-size distribution is fat-tailed, the central limit theorem does not hold, and thus idiosyncratic shocks do not cancel out in the aggregate (GABAIX, 2011). Other focuses on the presence of asymmetric intersectoral input–output linkages leading to sizable aggregate volatility from sectoral idiosyncratic shocks (ACEMOGLU et al., 2012).

Previous research focused on using aggregate shocks to explain business cycles, arguing that individual firm shocks average out in the aggregate if there is a large number of firms *N,* as positive shocks to some firms are offset by negative shocks to others. The granular hypothesis proposed by Gabaix (2011) challenges this view and its representative firm approach that implicitly assumes the existence of a certain level of homogeneity among the firms operating in the real world, a sort of average firm.

Granularity refers to the condition where a substance or system is composed of heterogeneous parts, or grains. Gabaix (2011) uses the notion of granularity as a business cycle theory of the behavior of large firms in the United States, the incompressible grains of the economy. Given that modern economies are made up of large companies, a considerable part of the aggregate fluctuations arise from their idiosyncratic shocks, rather than from diffuse shocks that directly affect all firms. Gabaix (2011) defines individual shocks as productivity shocks, but the analysis is valid for other shocks, such as revenue shocks.

Clarifying the observed fluctuation of economic aggregates is a popular topic of research in macroeconomics. A variety of potential reasons for variation in production are commonly given, such as stochastic variation in the timing of households' desired consumption of produced goods, or stochastic variation in the costs of production. But it is hard to see why there should be large and synchronized movements in those factors across the entire economy — why most households should want to consume less at exactly the same time, or why most firms should find it an especially opportune moment to produce at the same time. Instead, it seems more likely to suppose that variations in demand or in production costs in different parts of the economy should be largely independent (BAK et al., 1993).

The granular hypothesis also offers a microfoundation for the aggregate shocks of real business cycle models, in the sense that real business cycle shocks are no longer mysterious aggregate productivity shocks. Rather, they are well-defined shocks to individual firms. The granular hypothesis may bring us closer to a concrete understanding of the microeconomic composition of GDP, and the distribution of GDP and firm-level fluctuations (GABAIX, 2011). It may be a solid answer to Cochrane's (1994) question: "what are the shocks that drive economic fluctuations?".

Two measures are considered to investigate the granular hypothesis: 1) the "granular residual" is a parsimonious measure of the shocks to the largest companies in the economy. It explains about one third of the aggregate fluctuations in the U.S. economy between 1951 and 2008 (GABAIX, 2011); and 2) the "granular volatility" is a construct that can be used as an early warning system of GDP volatility (CARVALHO; GABAIX, 2013).

Gabaix (2011) argues that granular effects are likely to be even stronger outside the United States, as the American economy is more diversified than most other economies. For instance, direct and indirect impacts of Petrobras' investment contraction, Brazil's largest firm, may have exceeded 2 percentage points of GDP throughout 2014 and 2015. Da Silva et al. (2018) address the issue of granularity in the Brazilian economy and find that the size of firms in the country is power-law distributed, meaning that idiosyncratic shocks to big firms can lead to nontrivial aggregate shocks to GDP. However, they do not measure the impact of these shocks.

Therefore, the goal of this dissertation is to quantify the impact of idiosyncratic shocks to the largest Brazilian firms in GDP fluctuations. This has already been gauged in Europe (EBEKE; EKLOU, 2017), Spain (ARROYO; ALFARANO, 2017; BLANCO-ARROYO et al., 2018), Finland (FORNARO; LUOMARANTA, 2018), and Australia (MIRANDA-PINTO; SHEN, 2019), for example.

We use firm-level data on revenue for large non-financial Brazilian companies (sourced from *Exame* magazine and Economatica) to investigate whether the granular hypothesis holds for the Brazilian economy. In order to achieve this, we calculate the granular residual of the top 100 firms and regress GDP growth on it. Also, we compare the granular volatility with the aggregate volatility to check for the presence of an early warning system at work in the Brazilian economy. And we estimate the granular size of the Brazilian economy by considering Blanco-Arroyo et al. (2018)'s methodology, because until then the question of how many are the granular firms in an economy had been left unanswered. For instance, Gabaix (2011) chooses arbitrarily the top 100 firms.

This granular hypothesis may point to new paths for macroeconomic research in Brazil, in particular that macroeconomic questions can be elucidated by considering the behavior of large firms. For example, pondering on firm-level shocks improves our perception of GDP fluctuations, as the granular residual and the granular volatility can complement existing GDP predictors.

The remainder of this dissertation is organized as follows. Chapter 2 brings a theoretical background on the possibility of individual shocks to sectors or firms having aggregate effects. Chapter 3 presents the methodology employed in the study. Chapter 4 reports the results. And Chapter 5 concludes.

2 THEORETICAL BACKGROUND

There has long been a divergence of ideas in economic theory about the possibility of microeconomic shocks — those that affect a particular firm or sector of the economy — having real effects on aggregate variables.

Lucas (1977) argues there is a law of large numbers through which an individual shock to a given sector would be canceled out with shocks to different sectors of the economy. This argument is based on the assumption that new technologies or changes in consumer preferences reduce the production costs of the favored good or enable the production of a new one, thus attracting resources from the production of other goods. In a complex modern economy, there are a large number of such changes in any given period, each small in importance relative to total production, thus offsetting an aggregate movement. In other words, Lucas (1977) assumes an economy composed of homogeneous grains unable to generate changes in domestic output.

Real business cycle theorists, such as Kydland and Prescott (1982), Long and Plosser (1983) and Prescott (1986) argue that productivity shocks to some sectors can spread to the rest of the economy, causing recessions or booms. For example, Long and Plosser (1983) use a multisector model of the economy, with intermediate input linkages and uncorrelated sector-specific shocks. However, their model has some limitations as it assumes comovement of sector outputs even though the shocks driving productivity movements in each sector are independently distributed across them.

Bak et al. (1993) applied the theory of self-organizing criticality from physics in a multisector model to illustrate how the effects of many small and independent shocks are not canceled out in the aggregate due to two assumptions: 1) local interaction between productive units and 2) non-convex technology. They suppose that a large number of production units each buy goods from and sell goods to a small number of neighboring production units. The nonlinear interaction between these neighboring units' decisions results from non-convexities in the production technology that are important at the level of the production unit, though not on the scale of the aggregate economy. The exogenous shocks that drive the economy are independent fluctuations in flow demands for a large number of different types of final goods. The resulting distribution of levels of aggregate production converges to a Pareto-Lévy distribution. It is a distribution with the property that the probability of large events does not fall off exponentially with the size of the event. Thus, the law of large numbers does not apply and large events occur often in this scenario.

Horvath (1998) employs a multisector business cycle model and shows that, in the presence of limited interaction, about 80 per cent of U.S. GDP growth rate volatility may be the result of independent shocks to some sectors. This is because he assumes that a number of sectors are important suppliers of inputs, while others not. Horvath's (1998) analytical results show that aggregate volatility is amplified when the input-output matrix ischaracterized by only a few complete rows and many sparse columns. Full rows indicate sectors that provide important inputs to the production processes of many sectors. If there are few of these sectors, the effects of their specific shocks are less likely to be canceled out in the aggregate. The sparse columns indicate that most sectors' production processes are highly specific regarding to intermediate inputs. The impossibility of substitution between intermediate inputs forces sectors to react to shocks to the key input sectors in a similar way.

Such a matrix implies that few sectors serve as the main suppliers in the economy's production processes. As a result, idiosyncratic shocks that cause changes in factor prices of these sectors are important for the aggregate economy. In this situation, the law of large numbers does not apply because it depends on the number of full rows in the input-output matrix rather than the total number of rows in the matrix (number of sectors in the model economy).

Contrary to this view, Dupor (1999) argues that under the assumption that all sectors are suppliers of intermediate inputs to others, the way in which sectors interact (characterized by the input-output matrix) is irrelevant to the behavior of aggregate volatility. He claims that Horvath is able to generate large aggregate fluctuations only because he uses a moderate number of sectors (N = 36). The existence of highly disaggregated sectors makes aggregate volatility arising from sectoral shocks to approach zero due to the law of large numbers. Dupor (1999) concludes that if sector-specific shocks are indeed important for aggregate fluctuations, some other mechanism must be at work.

It is worth noticing that both rationales could be correct given that they deal with two different worlds. Horvath (1998) assumes that only a few sectors are important input suppliers, while Dupor (1999) assumes that every sector sells intermediate inputs to others sectors, making those sectors equally important as input suppliers.

Horvath (2000) expands his previous model to a dynamic general equilibrium in which aggregate fluctuations are driven by independent sectoral shocks. He assumes that intersectoral trade is a strong mechanism of shock propagation due to the limited, but locally intense, interaction of input trade flows. The reduced interaction characterized by a sparse input-output matrix dampens the possibilities of substitution between intermediate inputs, which strengthens the growth of sectoral value added and leads to a postponement of the law of large numbers in the variance of the aggregate value added.

Through a network perspective, Carvalho (2010) analyzes the flow of intermediate inputs between sectors. He argues that on the demand side, a typical sector relies on a small number of key inputs, and sectors are homogeneous in this regard. However, on the supply side many specialized input producing sectors coexist with general input sectors, which act as hubs for the economy. The intuition behind this hypothesis is that a shock to a general input producer sector, such as oil refineries, is likely to spread to the rest of the economy.

Thus, cyclical fluctuations in the aggregate are obtained as synchronized responses to changes in productivity of widely used input sectors. The number of sectoral connections originating from the source of the shock is the crucial variable to consider when determining whether a sectoral shock propagates or not (CARVALHO, 2010). If the number of connections varies widely between sectors, some shocks spread throughout the economy and persist over time, while others spread locally and have a short life. As a result, economies in which all sectors depend on a few sectoral hubs show considerable susceptibility to shocks to these technologies.

Following this line of research, Acemoglu et al. (2012) argue that in the presence of intersectoral input-output linkages, idiosyncratic shocks to a given sector may lead to aggregate fluctuations. They emphasize that as the economy becomes more disaggregated, the rate at which aggregate volatility decays is determined by the structure of the network that captures these links. The authors show that the structure of the intersectoral input-output relations of the US economy resembles a star network, as a small number of sectors play a disproportionately important role as input suppliers to others.

The results of Acemoglu et al. (2012) imply that sizable aggregate fluctuations can have two related causes. First, they may be due to shocks in one sector that is a supplier to a large number of other sectors. Secondly, they may be due to low productivity in one sector, which leads to a reduction in output not only of its immediate downstream sectors, but also of a sequence of interconnected sectors creating cascade effects. Unlike in Horvath (1998), the nature of aggregate fluctuations resulting from sectoral shocks is not related to the sparse input-output matrix but to the asymmetry between different sectors.

Thus, a recurring theme in the literature is that idiosyncratic shocks to a single sector can have sizeable aggregate effects if the sector is strongly interconnected with others in the economy. Gabaix (2011) suggests a more disaggregated analysis of microeconomic shocks. He pays attention to the role of individual firms in the aggregate business cycle. He argues that modern economies are dominated by large companies and when firm size is power-law distributed as a Zipf's law, idiosyncratic shocks to the big firms can lead to nontrivial aggregate shocks to GDP and, through general equilibrium or supply chain linkages, to all firms in the economy.

The effect of individual firm shocks on aggregate fluctuations will be more relevant the higher the sales Herfindahl index (a measure of market concentration). Gabaix's hypothesis of granularity gauges through a measure called granular residual, that idiosyncratic movements of the top 100 American firms in terms of sales — the big grains — explain about one-third of the variations in U.S. output growth over the period 1951-2008.

Following the trend of deeper disaggregation, Di Giovanni and Levchenko (2012) calibrate and simulate a multicountry model of firm-level production and trade from the world's 50 largest economies that can generate granular fluctuations. They show that the contribution of international trade to aggregate volatility varies a great deal depending on country characteristics. Like Gabaix (2011), they argue that when firm size distribution is fat-tailed and follows a power law with an exponent close to one, idiosyncratic shocks to the large companies impact aggregate volatility.

The results obtained by Di Giovanni and Levchenko (2012) show that there is a negative relationship between size of the economy and aggregate volatility. The reason is that smaller economies have fewer firms, so shocks to the larger companies will be more important to aggregate volatility. In their model, trade openness increases volatility, making an economy more granular, because when a country opens up to trade, only the largest and most productive firms export, while the small firms shrink or disappear. This effect implies that after opening, the biggest companies become even larger relative to the size of the economy, thus contributing more to aggregate output fluctuations.

Adopting the granular hypothesis, Carvalho and Gabaix (2013) propose a simple structure to predict U.S. GDP volatility, which they call "fundamental volatility" (or granular volatility), a volatility that does not require the knowledge of detailed linkages as it is derived only from microeconomic shocks. The insight is that aggregate shocks come largely from microeconomic shocks, augmented by amplification mechanisms. Therefore, aggregate volatility should track granular volatility.

They use this formulation to explain the Great Moderation period of the American economy (1984-2007). The authors' methodological principle is to use the simplest and most transparent approach possible, thus avoiding the use of infinite horizon dynamic stochastic general equilibrium (DSGE) models and the rigidity of input-output matrices that assume fixed coefficients and constant returns to scale.

Because of the simple and efficient structure of granularity, many have replicated it to other countries. Wagner (2012) shows that idiosyncratic shocks to the largest firms are important to understand aggregate volatility in German manufacturing industries. His results indicate that the German manufacturing sector is fat-tailed distributed.

Di Giovanni, Levchenko and Mejean (2014) employ data of French firms from 1990 to 2007 to build a multisector model of heterogeneous firms selling to multiple markets and motivate a decomposition of firms' annual sales growth rate into different components (macroeconomic, sectoral and firm-level). They find that the firm-specific component contributes to aggregate sales volatility about as much as the components capturing shocks that are common across firms within a sector or country. Also, they suggest two mechanisms generating aggregate fluctuations: 1) when firm size distribution is fat-tailed, idiosyncratic shocks to large firms contribute directly to aggregate fluctuations, and 2) aggregate fluctuations can arise out of idiosyncratic shocks due to input-output linkages across the economy.

Ebeke and Eklou (2017) contribute to this literature by considering a database of the 100 largest firms of eight euro area countries (Austria, Belgium, Finland, France, Germany, Italy, Portugal and Spain) for the period 2000-2013. Their results indicate that the granular residual explains 40 per cent of GDP growth fluctuations in the sample and it is also important to interpret other variables such as investment, exports and unemployment.

Arroyo and Alfarano (2017) and Blanco-Arroyo et al. (2018) examine the existence of granularity in the Spanish business cycle fluctuations over the 1999-2014 and 1995-2016 periods, respectively. Their analysis reveals that depending on the specification, half of the variation in GDP growth may be linked to the idiosyncratic shocks from the top 100 Spanish firms.

Fornaro and Luomaranta (2018) investigate whether the granular hypothesis can be applied to the Finnish economy. They calculate the granular residual from monthly, quarterly and annual revenue data of the 57 largest enterprise groups between 1998 and 2013. Their results reveal that idiosyncratic shocks to these firms account for about one-third of GDP fluctuations. In particular, the four largest firms play a major role.

Miranda-Pinto and Shen (2019) explore the hypothesis of the granular origins of business cycle fluctuations for the Australian economy. They show that firm size distribution in Australia follows a power law, with a few firms being disproportionately large. They also document that shocks to a small number of large non-financial firms account for a large share (20–40 per cent) of the fluctuations in Australian GDP growth for the period 2000–2018.

Da Silva et al. (2018) test the hypothesis of granularity for the Brazilian economy by adjusting a power law to net revenue data of the 1,000 largest Brazilian firms in 2015. The authors conclude that they cannot reject a Zipf's law. An interesting development from the result that the size distribution of Brazilian firms follows a Zipf's law is the possibility to measure both the granular residual and the granular volatility.

The granular hypothesis can also be applied to other economic variables. For example, Del Rosal (2013) investigates whether granular structure is present in product exports from 11 European Union countries from 1988 to 2011. They define granularity as the high concentration of country exports in the top products. Their results suggest that idiosyncratic shocks to major products can have significant effects on total exports for smaller and less diversified economies, in particular those of Greece, Portugal and Ireland.

Del Rosal (2018) extends his analysis for 28 European Union countries over the period 2002–2014. He fits power laws running log of rank–log of size regressions of exports at the product exported level. He finds negative correlation between volatility in E.U. country exports and export diversification. Thus, idiosyncratic shocks to the top products do not average out in the aggregate and affect the evolution of country exports.

Friberg and Sanctuary (2016) analyze the volatility of Sweden's exports over the 1997-2008 period, concluding that firm-specific shocks are significant. Blank, Buch, and Neugebauer (2009) construct a banking granular residual and find that negative shocks to large banks negatively impact smaller banks.

Dosi et al. (2019) argue that Gabaix's (2011) "supply" granularity — as proxied by productivity growth shocks — should be replaced by a "demand" granularity, based on investment growth shocks. They claim that their investment growth granular residual provides a good explanatory power and shows a positive impact on GDP growth.

In sum, this dissertation is closely related to the literature that studies the origin of aggregate fluctuations arising from microeconomic shocks, more specifically to the groundbreaking work of Gabaix (2011) and Carvalho and Gabaix (2013), as we look to the aggregate output fluctuations in the Brazilian economy from the granular structure perspective.

3 METHODS AND DATA

This dissertation is an empirical research that aims to identify microeconomic factors that may explain aggregate fluctuations, such as idiosyncratic shocks to large firms in a country. Two measures are used: the first is the granular residual proposed by Gabaix (2011), while the second is the granular volatility suggested by Carvalho and Gabaix (2013). Throughout, we present results on annual data, because it is more relevant for the questions of macroeconomic fluctuations (ACEMOGLU; AKCIGIT; KERR, 2016).

3.1 Granular residual

Modern economies are dominated by large firms, so idiosyncratic shocks to these firms can lead to nontrivial aggregate shocks. In this sense, many economic fluctuations are not primarily due to widespread small shocks that directly affect all companies. Rather, many economic fluctuations are attributable to the incompressible "grains" of economic activity, the large corporations (GABAIX, 2011) . This granular hypothesis offers a microfoundation for the aggregate shocks of real business cycle models, such as Kydland and Prescott (1982), in that these shocks are no longer mysterious aggregate productivity shocks, but well-defined shocks to individual companies.

Gabaix (2011) assumes that the standard deviation of a company's revenue growth rate is independent of its size. This explains why individual companies can affect the aggregate. He shows that the central limit theorem breaks down in an economy with firms that are fat-tailed distributed. The central limit theorem establishes that in an economy with N firms with independent shocks, the aggregate fluctuations must have a size proportional to $1/\sqrt{N}$. Given that modern economies can have millions of firms, this means that idiosyncratic fluctuations have a negligible aggregate effect.

However, Gabaix (2011) points out that when the size of firms follows a fat-tailed distribution, the conditions under which the central limit theorem is derived break down, as power laws emerge. Axtell (2001) states that firm size in industrial countries is highly skew, such that a small number of large firms coexist alongside a larger number of smaller firms. Such skewness has been robust over time, being insensitive to changes in political and regulatory environments, immune to waves of mergers and acquisitions, and unaffected by surges of new firm entry and bankruptcies. It has even survived large-scale demographic transitions in labor force (such as, women entering the labor market in the United States) and widespread technological change.

Da Silva et al. (2018) find that the size distribution of the top 1,000 Brazilian firms is well approximated by a power law with exponent v = 1, the Zipf distribution, in which case aggregate volatility decays according to $1/\ln N$ instead of $1/N$,which means a much milder decay.

Because the microeconomic shocks do not disappear in the aggregate, the granular residual shows the proportion of aggregate shocks that can be attributed to idiosyncratic movements. Here, the key challenge is to identify firm-level shocks, for example, the beginning of a strike, the launch of a new product, or the sales of a big export contract. Presumably, these events take some time to spill over into the rest of the economy. At the same time, large firms could be volatile precisely because of the aggregate shocks, rather than the other way around, and there is no general solution for this "reflection problem" (MANSKI, 1993).

The granular residual (Γ_t) is a parsimonious measure of the shocks to Brazil's largest K firms:

$$\Gamma_t = \sum_{i=1}^{K} \frac{R_{i,t-1}}{GDP_{t-1}} (g_{it} - \overline{g}_t), \tag{1}$$

where $R_{i,t-1}$ denotes the deflated (with IPCA) net revenue of firm i at the time $t-1$, GDP_{t-1} is the deflated (with GDP deflator) Brazilian gross domestic product, and $g_{it} - \overline{g}_t$ is the measure of idiosyncratic shock to firm i, which is computed as:

$$g_{it} = \ln(R_{i,t}) - \ln(R_{i,t-1}) \tag{2}$$

and

$$\overline{g}_t = Q^{-1} \sum_{i}^{Q} g_{it}, \tag{3}$$

where $K \leq Q$ (the number of firms in the economy). This metric essentially removes any aggregate shocks affecting all firms equally by demeaning firm-level revenue growth.

The metric for the impact of firm i is its size, as measured by its weight (that is, revenues divided by gross domestic product). To justify this, Gabaix (2011) uses an important feature of models of complementarity, that is, a Hicks-neutral productivity shock increases sales (gross output), not just value added (DOMAR, 1961; JONES, 2011).

Gabaix (2011) divides the firms' revenues by the number of employees in a year to track individual productivity shocks. However, this sort of microdata is not available for all Brazilian companies in our sample. For this reason, we choose to use only firm revenue shocks, such as in Di Giovanni, Levchenko and Mejean (2014), Stella (2015), Fornaro and Luomaranta (2018) and Miranda-Pinto and Shen (2019). Revenue shocks are important because they affect the financial structure of the firm and thus have persistent effects on firm size, growth, and probability of survival (CLEMENTI; HOPENHAYN, 2006).

Cardoso and Portela (2009) argue that revenue is a good indicator of firm performance, because it captures demand uncertainty, as shocks in product demand are directly reflected in changes in sales. And given fluctuations in demand, output could remain unchanged if prices would adjust fully and instantaneously; however, since that is not observed, output undergoes fluctuations (BAILY, 1974).

An alternative to (1) is to compute the granular residual by using the deviation of the growth rate of revenues from the industry specific averages ($\bar{g}_{I_i t}$), where I_i indicates the industry that firm i operates. Thus,

$$\overline{\Gamma}_t = \sum_i^K \frac{R_{i,t-1}}{GDP_{t-1}} (g_{it} - \overline{g}_{I_i t}). \tag{4}$$

and

$$\overline{g}_{I_i t} = J^{-1} \sum_i^J g_{I_i t}, \tag{5}$$

where J is the number of companies in the industry that firm i operates.

After obtaining an estimate for the granular residual, we regress Brazilian GDP growth on the granular residual and its lags:

$$GDP\ growth_t = \beta_0 + \beta_i \Gamma_{t-p} + u_t, \tag{6}$$

with p = 0, 1, …, n. Here u_t is the error term, which we assume normally distributed and uncorrelated with the regressors.

We evaluate the explanatory power of (1) and (4) using the adjusted R^2. When Gabaix (2011) regresses the growth rate of U.S. GDP on the granular residual of the 100 largest firms, he gets an adjusted R^2 of approximately one third. This means idiosyncratic shocks to the top 100 U.S. companies can explain one-third of the fluctuations of American GDP.

3.2 Granular volatility

Carvalho and Gabaix (2013) derive a formal two-period model with microeconomic foundations to construct a new indicator, called granular volatility (σ_{Gt}). They compute and compare it to the volatility of GDP growth in the United States from 1960 to 2009, United Kingdom, France and Germany from 1970 to 2005, and Japan from 1973 to 2005. Here, this measure is calculated for Brazil from 1999 to 2016 using:

$$\sigma_{Gt} = \sqrt{\sum_{i}^{K} \left(\frac{R_{it}}{GDP_t} \right)^2 \sigma_i^2}, \tag{7}$$

where $R_{i,t}$ denotes the deflated net revenue of firm i at the time t, GDP_t is the Brazilian deflated gross domestic product and σ_i stands for the firm-level volatility (see equation 12). After calculating the granular volatility, the GDP growth volatility is computed as:

$$\sigma_{Yt} = \mu \cdot \sigma_{Gt}, \tag{8}$$

where the productivity multiplier μ is equal to

$$\mu = \frac{1+\phi}{\alpha}, \tag{9}$$

where α is the labor share, and ϕ is Frisch elasticity of labor supply. Carvalho and Gabaix (2013) suggest to use Frisch elasticity because it considers not only changes in hours worked per employee but also changes in employment and effort.

The values of these parameters are collected from calibrations already performed in the Brazilian literature. Then, we analyze graphically the adjustment of (7) to the GDP volatility estimate obtained by econometric methods to evaluate the cyclical volatility.

3.3 Data description

An empirical test on a theory depends crucially on the quality and detail of the available data. Because of database limitations in Brazil, annual data was collected from *Exame* magazine, which provides net revenue information for the 500 largest Brazilian companies since 1999. We also use a different sample by collecting quarterly data from Economatica, which presents data for publicly listed companies in Brazil. In order to reduce under- or over-representation, we opt to gather information from the first quarter of 1997 because this is the first quarter from which net revenue is available for at least 100 firms. However, there are still some striking differences between annual and quarterly data. For instance, considering the top 100 Brazilian firms in 2018, the most represented industries in annual data are: oil and energy (15%), wholesale (14%), consumer goods (11%), retail (11%), and automotive (9%), while in quarterly data, the most represented industries are: oil and energy (30%), transportation (8%), retail (7%), service (7%), and wholesale (6%) (see appendix for more descriptive statistics).

It is important to notice that our results are robust to most of Dosi et al. (2019)'s criticisms. These authors replicated the calculations in Gabaix (2011) and find that Gabaix's results rest on some methodological assumptions, such as: 1) the granular hypothesis discusses the role of firm shocks on the business cycle, but only GDP per capita growth is employed as the dependent variable, whereas the results should have been tested using GDP growth; 2) the granular residual is based on a normalization on the average of the top firms and not on the whole sample; 3) the microdata are subject to quite extreme data cleaning, that is, outliers are eliminated at the 20th and 80th percentiles, whereas the common procedure is to clean the data by removing observations below the 1st and above the 99th percentiles.

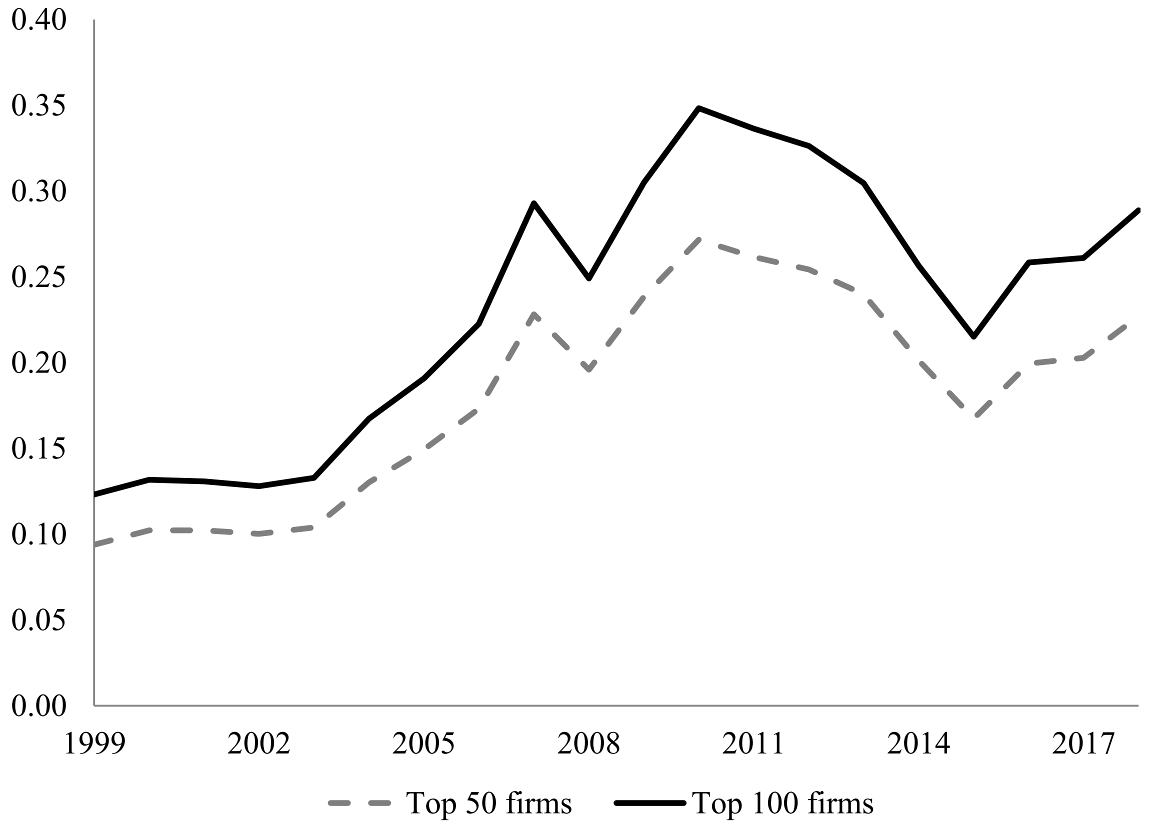
According to Dosi et al. (2018), if these assumptions are dropped, Gabaix's model loses significance and its explanatory power is dramatically reduced. So, there is a paradox: granular shocks appear to be important only if one assumes from the start that the shocks themselves are not fat-tailed. Here in this dissertation, we do not "winsorize" our data by removing extreme shocks, we use GDP growth as the dependent variable and further normalize the shocks on the average of the whole sample to link the performance of a firm to the overall economy.

4 EMPIRICAL RESULTS

4.1 The granular residual and the Brazilian economy

Figure 1 displays the sum of net revenues of the 50 and 100 largest Brazilian firms as a proportion of GDP from 1999 to 2018. On average, the revenues of the top 50 companies are 18 per cent of GDP, while the revenues of the top 100 companies are 24 per cent. This percentage remains relatively low during the first years of the sample. Between 2004 and 2007, the proportion increases considerably, reaching 30 per cent for the top 100 firms. In 2008, the upward trend of participation is reversed, but then goes back to the previous path in the subsequent year, peaking in 2010. Afterwards, we observe a downward trend until 2015 and then a recovery. This last period is marked by a deep recession over 2015 and 2016 and a subsequent sluggish growth. With the failing GDP, the large firms' share expanded.

Figure 1. Sum of the net revenues of the top 50 and 100 Brazilian firms as a fraction of GDP (1999-2018).



Because the lion's share of the Brazilian economic activity belongs to the top 100 companies, understanding their actions is important for a good understanding of the aggregate economy. A striking curiosity is that, on average, the sales of the top 100 American (GABAIX, 2011) and euro area (EBEKE; EKLOU, 2013) firms represent about 29 per cent of GDP, namely a larger fraction when compared to Brazil's 24 per cent, a smaller economy.

Considering the measure of concentration given by the squared Herfindahl index:

$$h = \left(\sum_{i=1}^{N} \left(\frac{R_{it}}{GDP_t} \right)^2 \right)^{\frac{1}{2}}, \tag{10}$$

Gabaix (2011) finds h = 5.3 per cent for the United States in 2008; Blanco-Arroyo et al. (2018) find h = 4.8 per cent for Spain from 1995 to 2016, while for Brazil over the period 1999-2018, we find h = 4.3 per cent on average (N = 500). This means that Brazil is a country with relatively more small firms (when compared to GDP), and the granular hypothesis might be more difficult to establish.

We first check whether the Brazilian economy is granular by computing the explanatory power of the granular residual for the top 100 firms. For now, we choose K = 100 in order to compare the result to the international literature. The number of lags is selected according to Akaike and Schwarz's information criteria, but also considering the degrees of freedom.

Table 1. Explanatory power of the granular residual.

	Top 100 (Q = 100)		Top 100 (Q = 500)	
	(1)	(2)	(3)	(4)
Γ_t	3.485***	1.153*	2.864**	1.310*
	(0.743)	(0.685)	(0.512)	(0.679)
Γ_{t-1}		5.355***		3.151***
		(1.119)		(0.804)
(Intercept)	0.017***	0.048***	0.045***	0.039***
	(0.005)	(0.005)	(0.004)	(0.006)
N	19	18	19	18
R^2	0.229	0.422	0.398	0.397
Adjusted R^2	0.183	0.344	0.363	0.317

Notes: For the year t = 2000 to 2018, GDP growth is regressed on the granular residual Γ_t of the top 100 firms using (1). The firms are the largest by net revenues of the previous year. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 1 presents ordinary least squares (OLS) regressions of annual GDP growth on the simplest granular residual (1), taking into account the top 100 Brazilian companies (K =

100) over the period 1999-2018. These regressions present results very similar to those of Gabaix (2011) for the United States, Ebeke and Eklou (2013) for Europe, Fornaro and Luomaranta (2018) for Finland, and this means the granular hypothesis for Brazil is in line with the international evidence. The adjusted R^2s are reasonably high, at 34.4 per cent when we consider one lag and use $Q = 100$, and at 36.3 per cent when we take $Q = 500$.

Therefore, idiosyncratic movements in the net revenues of the 100 largest Brazilian firms explain a large part (about one-third) of GDP fluctuations. In other words, the top 100 companies account for more variation in GDP growth than their average share. So, the effects of individual shocks may propagate throughout the economy, instead of remaining confined to where they originate.

If only the aggregate shocks were important, the R^2 of the regressions in Table 1 would be zero. Our results could suffer from reverse causality, namely that if an aggregate shock drives both aggregate GDP and firm revenues, it is natural to observe a positive correlation between the granular residual and the GDP growth. To rule out reverse causality, we calculate the sample correlation of the net revenue growth rates of the 100 largest firms for each year t:

$$\rho_t = \frac{\left[\frac{1}{K(K-1)}\sum_{i \neq j} g_{it} g_{jt}\right]}{\left[\frac{1}{K}\sum_{i} g_{it}^2\right]}. \tag{11}$$

Taking every year into account, we find 0.065, which is significantly small. As a result, it can be argued that much of the variation in firm revenues is, in fact, idiosyncratic. A high correlation between firm-level shocks would indicate that an aggregate shock drives both GDP and firm-level performance.

The industry demeaning model might give us a more appropriate estimate of the granular residual, so we re-estimate the linear regression using (4) as an explanatory variable. Table 2 presents the results.

The granular residual has positive and statistically significant coefficients, and it is able to explain a substantial portion, nearly twenty per cent, of Brazilian business cycle fluctuations when we do not include a lag. However, the adjusted R^2 is somewhat lower than the ones in Table 1, a finding in line with Fornaro and Luomaranta (2018) for Finland, but opposite to those found by Gabaix (2011) for the United States and Arroyo and Alfarano (2017) for Spain.

Table 2. Explanatory power of the granular residual, industry demeaned.

	$GDP\ growth_t$	
	(1)	(2)
$\overline{\Gamma}_t$	2.146***	1.980***
	(0.715)	(0.873)
$\overline{\Gamma}_{t-1}$		-0.312
		(1.044)
(Intercept)	0.038***	0.035***
	(0.006)	(0.009)
N	19	18
R^2	0.236	0.133
Adjusted R^2	0.191	0.017

Notes: For the year t = 2000 to 2018, GDP growth is regressed on the granular residual $\overline{\Gamma}_t$ of the top 100 firms using (4). The firms are the largest by net revenues of the previous year. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

4.2 Robustness check: quarterly data

Due to the short time span of our annual time series, we could incur small sample problems. Despite some authors in the literature using a smaller or similar number of years — such as Arroyo and Alfarano (2016) (N = 14), Ebeke and Eklou (2017) (N = 14), and Blanco-Arroyo et al. (2018) (N = 22) — we opt to cautiously collect higher frequency data from Economatica to expand our time series.

As discussed by Fornaro and Luomaranta (2018), microeconomic level shocks are likely to have a large effect in the short run, but their impact on aggregate fluctuations might be attenuated when considering data at lower frequencies. For example, a strike in one company occurring during a certain month can have a substantial effect on the aggregate output for that period, but its impact might vanish when considering the whole year, due to time aggregation. One advantage of using quarterly data is that it allows us to verify the granular hypothesis for different subsamples and to examine if any events have affected it.

Table 3 reinforces the conclusion that idiosyncratic movements from the top 100 firms can explain a significant fraction of GDP fluctuations, that is 21.3 per cent. However, the granular residual loses explanatory power when compared to its annual counterpart. It could be a consequence of the distinct sample, given that we are dealing with only the largest publicly listed companies.

Once again, to rule out reverse causality we calculate the sample correlation of the net revenue growth rates of the 100 largest firms for each quarter q. The result found is 0.047, which is again significantly small. Therefore, much of the variation in firm revenues is, in fact, idiosyncratic.

Table 3. Explanatory power of the quarterly granular residual.

	GDP growth$_t$	
	(1)	(2)
Γ_t	0.806***	0.795***
	(0.164)	(0.176)
Γ_{t-1}		-0.178
		(0.132)
(Intercept)	0.015***	0.013***
	(0.004)	(0.003)
N	87	86
R^2	0.222	0.233
Adjusted R^2	0.213	0.214

Notes: For the quarter q = 1997Q2 to q = 2018Q4, GDP growth is regressed on the granular residual Γ_t of the top 100 firms using (1). The firms are the largest by net revenues of the previous quarter. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

A larger decrease of explanatory power occurs when we analyze the industry demeaned granular residual using (4). Table 4 reports the results. The granular residual now explains less than 10 per cent of GDP fluctuations, but it remains positive and statistically significant. The time frequency of the data might explain this aspect. Quarterly data are intrinsically more volatile compared to annual ones. Therefore, it is worthwhile considering different subsamples to search for possible divergences.

Table 4. Explanatory power of the quarterly granular residual, industry demeaned.

	GDP growth$_t$	
	(1)	(2)
$\overline{\Gamma}_t$	0.418***	0.399**
	(0.133)	(0.168)
$\overline{\Gamma}_{t-1}$		-0.108
		(0.135)
(Intercept)	0.013***	0.011***
	(0.004)	(0.004)
N	87	86
R^2	0.104	0.109
Adjusted R^2	0.093	0.088

Notes: For the quarter q = 1997Q2 to q = 2018Q4, GDP growth is regressed on the granular residual $\overline{\Gamma}_t$ of the top 100 firms using (4). The firms are the largest by net revenues of the previous quarter. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p<0.01.

4.3 Time-varying contribution of the granular residual

Brazil presented consistent growth in the years prior to the American Great Recession, and then registered a drop in GDP in 2009. Afterwards, it showed a massive recovery in 2010, which was followed by sluggish growth, a deep recession in the 2015-2016 period and a subsequent sluggish growth until 2018. We cannot reject the hypothesis that the Great Recession represents a breaking point for the Brazilian economy and for many of its largest firms as it seems to have occurred in Finland (FORNARO; LUOMARANTA, 2018).

Table 5. Explanatory power of the quarterly granular residual.

	GDP growth$_t$				
	Pre-2009		Pre-2015		Post-2009
Γ_t	1.027***	0.991***	0.899***	0.887***	-1.334
	(0.206)	(0.202)	(0.164)	(0.187)	(0.899)
$\Gamma_{t\text{-}1}$		-0.227***		-0.135	
		(0.076)		(0.135)	
(Intercept)	0.026***	0.022***	0.020***	0.019***	0.004
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
N	47	46	71	70	40
R^2	0.546	0.571	0.303	0.309	0.064
Adjusted R^2	0.536	0.551	0.293	0.289	0.040

Notes: GDP growth is regressed on the granular residual Γ_t of the top 100 firms using (1). The firms are the largest by net revenues of the previous quarter. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 6. Explanatory power of the quarterly granular residual, industry demeaned.

	GDP growth$_t$		
	Pre-2009	Pre-2015	Post-2009
$\overline{\Gamma}_t$	0.844***	0.563***	-0.389
	(0.134)	(0.138)	(0.244)
(Intercept)	0.026***	0.018***	0.005
	(0.005)	(0.005)	(0.006)
N	47	71	40
R^2	0.467	0.193	0.062
Adjusted R^2	0.455	0.182	0.038

Notes: GDP growth is regressed on the granular residual $\overline{\Gamma}_t$ of the top 100 firms using (4). The firms are the largest by net revenues of the previous quarter. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p<0.01.

In the face of it, we analyze a pre-recession period, from the first quarter of our sample until the last quarter of 2008, and a sample covering the remaining years up to the last quarter of 2018. We also examine the data from the beginning of our sample until the last quarter of 2014 to disregard the effects of the recession of 2015-2016.

In Tables 5 and 6, we report the results for metrics (1) and (4) using the pre- and post-recession subsamples, respectively. The granular hypothesis seems to break down with the Great Recession of 2008–2009. While the granular residual accounts for a large portion of output variation over the whole period up to the Great Recession, its explanatory power is greatly reduced thereafter. It appears that the deep recession in the period 2015-2016 also contributes to the loss of explanatory power.

The results indicate an abrupt distinction between the pre- and post-Great Recession periods regarding the granular hypothesis. Prior to 2009, we find that the granular residual is able to explain a great portion of real output variation, with the adjusted R^2 consistently around 0.5. Moreover, the coefficients associated with Γ_t are highly significant and positive. However, Tables 5 and 6 shows the Great Recession changes our results dramatically. The granular hypothesis does not seem to hold for the years after the Great Recession. The portion of explained variance becomes null or very small for all specifications and the coefficients become negative and statistically nonsignificant.

This retraction in the explanatory power of the granular residual is extremely interesting and resembles the one occurred in Finland, as reported by Fornaro and Luomaranta (2018). One possible explanation behind this result could be that the aggregate shocks are the driving force of the Brazilian economy for the post-Great Recession period.

A new macroeconomic regime started from 2011 onwards, which was characterized by an easing of fiscal and monetary policies to boost aggregate demand and stimulate growth and capital accumulation. From the second semester of 2011 to the first semester of 2013, nominal interest rates as well as taxes over manufactured products were reduced. The consequences were a very modest increase in GDP growth rate in 2013 as compared to 2012, at the expense of inflation acceleration and a reduction in the primary surplus of federal government (OREIRO, 2015).

By the end of 2014, a political crisis erupted after the imprisonment of hundreds of businessmen — several from some of the largest firms — and their parliamentary allies. This was followed by the impeachment of the Brazilian President in 2016 and the subsequent arrest of the then speaker of the House of Commons.

Other variables, such as investment, could be the driving force after the Great Recession. It would be interesting to take into account the role of demand in explaining the aggregate fluctuations during economic downturns along the lines suggested by Dosi et al. (2019).

Apart from these caveats, the shocks affecting large firms seem to have had a substantial impact on real economic activity on sample period considered, except for the post-2008 years. Possibly, after economic downturns the granular hypothesis seems to weaken.

In order to verify precedence, we run Granger causality tests with both granular residuals (1) and (4). Table 7 reports the results.

Table 7. Granger causality tests (quarterly granular residual).

Null Hypothesis	Pre-2009		Pre-2015		Post-2009	
	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.
Γ does not Granger cause GDP growth	13.294	0.009***	3.567	0.467	14.675	0.005***
GDP growth does not Granger cause Γ	5.072	0.280	5.758	0.218	8.031	0.09*
$\overline{\Gamma}$ does not Granger cause GDP growth	7.332	0.119	3.160	0.531	7.131	0.129
GDP growth does not Granger cause $\overline{\Gamma}$	2.221	0.695	5.898	0.207	0.747	0.945
N	43		67		40	

Notes: The number of lags used in the test regressions is 4, selected according to the Akaike and Schwarz information criteria. *p < 0.10, **p < 0.05, ***p < 0.01.

For the industry-demeaned granular residual (4), we cannot reject the null hypotheses all periods considered. When we run the test for the pre-2009 period for the other granular residual (1), we reject the null hypothesis that Γ does not Granger cause GDP growth, as expected by the results presented in Table 5. We reject the same null hypothesis for the post-2009 period. Therefore, current GDP growth can be explained by past values of the granular residual (1) as assumed by the granular hypothesis. However, the null hypothesis that GDP growth does not Granger cause Γ is also rejected for the post-Great Recession period. Perhaps this two-way relationship is another indication that aggregate shocks matter the most in economic downturns, diminishing the importance of idiosyncratic shocks, and in consequence of the granular hypothesis.

4.4 Computing the granular volatility

Assuming the aggregate shocks arise from microeconomic shocks, then aggregate volatility should track granular volatility. Because the top 100 firms are very large, most of the variation in σ_{Y_t} is driven by them (CARVALHO; GABAIX, 2013). To examine if this occurs in Brazil, it is necessary to compute the granular volatility (6) and compare it with estimates of aggregate volatility.

For firm-level volatility σ_i, a firm-by-firm estimation yields quite volatile numbers, so we decide to take the a constant value of 5.36 per cent across firms. This value is reached by taking the average standard deviation of the cross-sectional variance of growth rates:

$$\sigma_t^2 = K^{-1}\sum_i^K g_{it}^2 - \left(K^{-1}\sum_i^K g_{it}\right)^2, \tag{12}$$

with $K = 100$.

The average standard deviation is equal to:

$$\overline{\sigma}_{sd} = \left(K^{-1}\sum_i^K \sigma_t^2\right)^{\frac{1}{2}}. \tag{13}$$

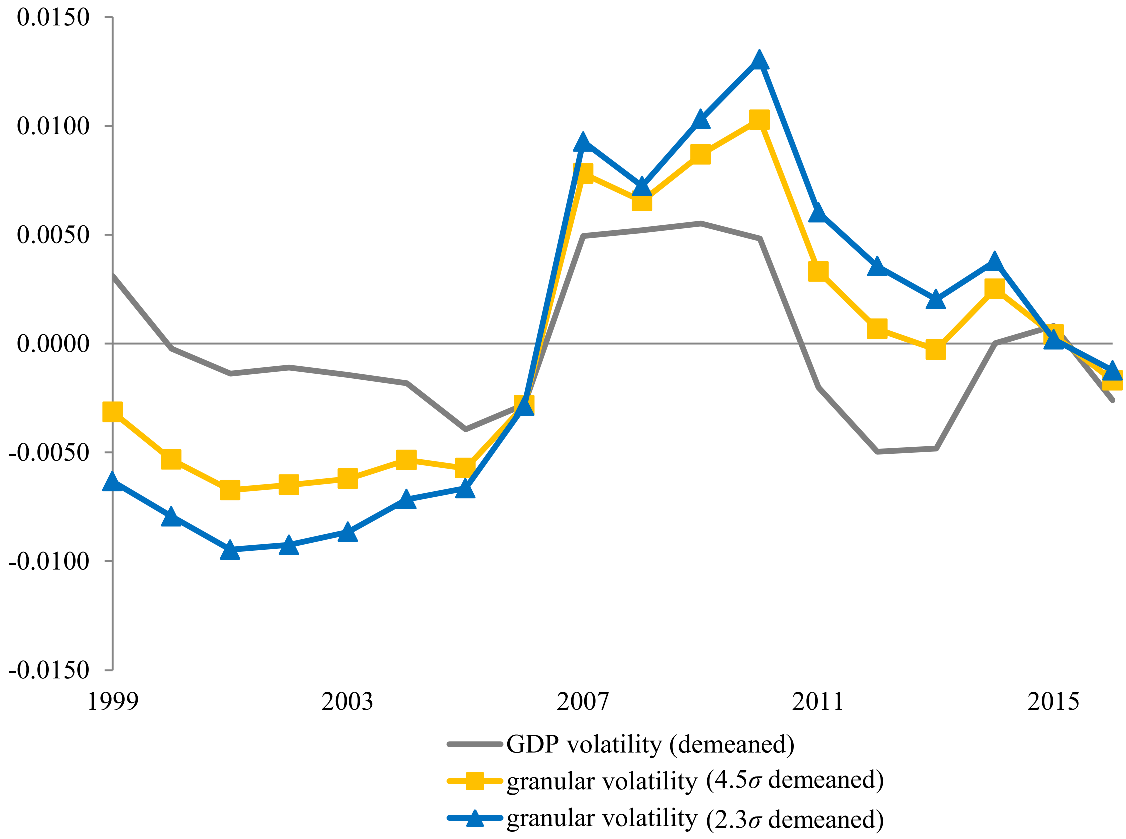
The labor share α used is 0.5422, which is obtained by averaging this indicator between 2000 and 2014, available for Brazil from the Penn World Table. Moura (2015) and Costa Filho (2015) find values close to 0.25 for Frisch elasticity of labor supply ϕ in the Brazilian economy. With the values shown above, Brazil's productivity multiplier μ is 2.3. Alternatively, the value found by Carvalho and Gabaix (2013) of 4.5 for this multiplier is also employed. The granular volatility is calculated after calibrating using these values.

A baseline estimate of cyclical volatility (GDP volatility) is calculated using the trend deviations obtained by the Hodrick-Prescott filter of quarterly real GDP (smoothing parameter = 1,600; sample from 1995:Q1 to 2018:Q4). Standard deviation for the quarter q is computed with a continuous 16-quarter window, centered on the quarter of interest. To construct the volatility of a given year t, the average is calculated over the four quarters of that year. Because of this rolling window and data limitation, aggregate volatility can only be obtained between 1999 and 2016.

Figure 2 plots the evolution of the Brazilian granular volatility for the two values of σ_{Yt}, both demeaned. The granular volatility seems to capture well the different movements in GDP volatility. For the two values of μ, it remains negative and stable until 2005, and then rises to a peak in 2010. Afterwards, it begins to fall, approaching to its mean. The cyclical volatility, also demeaned, shows a similar swing trajectory around its mean: a smooth negative trend until 2005, a rise to its maximum during 2007-10, an intense decline trend afterwards, a gradual upward trend towards its mean, only to finish with another decreasing tend.

Because of the small time series sample (N = 18), we cannot establish a statistical relationship, but it is intriguing to look at Figure 2 and conjecture whether the granular volatility works as an early warning system of aggregate volatility in Brazil.

Figure 2. Brazilian granular and GDP volatilities, 1999-2016.



4.5 Determining the granular size of the Brazilian economy

One criticism to Gabaix's (2011) granular hypothesis is the arbitrary definition of the number of firms that are critical to explain aggregate fluctuations (K = 100). To overcome this difficulty, Blanco-Arroyo et al. (2018) propose a methodology to calibrate the number of companies relevant to the calculation of the granular residual. They take Spain as an illustrative case and estimate approximately 450 granular firms.

A granular firm is characterized by the fact that its idiosyncratic shocks have a significant impact on GDP growth fluctuations. Despite the fact that granular firms constitute just a small fraction of the total number of firms, they are responsible for the lion's share of business cycle fluctuations.

Blanco-Arroyo et al. (2018) point out that the identification of the economy as a granular economy is based on an exogenous choice for the number of large firms as in (1).

Such estimation of the R^2 does not provide information on the extent of the granular region given that the number of firms considered is arbitrarily chosen. Therefore, we may underestimate the contribution of the granular residual to GDP fluctuations, considering too few granular firms, or overestimate its impact, including too many firms as in (5).

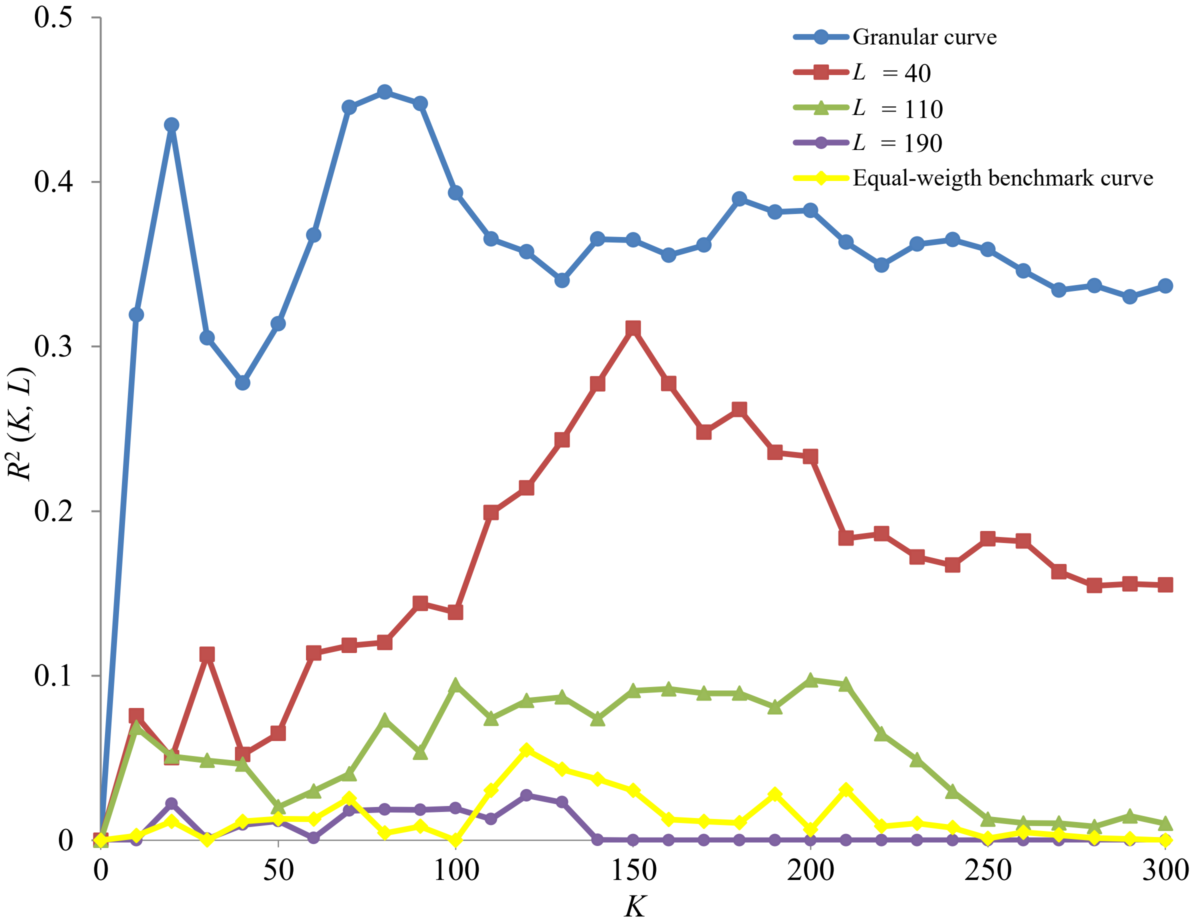
Having this in mind, the goal is then to optimally calibrate the number of granular firms, K^*. We first investigate how the explanatory power of the annual granular residual behaves when we gradually increase K in (1) within the range $1 \leq K \leq Q = 300$. Figure 3 shows the evolution of R^2. We call the upper curve in Figure 3 the "granular curve". This curve is characterized by: 1) a sharp increase of R^2 when from a reduced number large firms are progressively considered in the calculation of the granular residual (roughly the largest 20 firms); 2) a swing in the value of R^2 when including the next 80; 3) a stable value of R^2 when inserting additional firms.

To endorse our results, we introduce an equal weight benchmark by replacing the empirical weights in (1) with constant weights for all firms, that is, fixing $S_{it} = S_t^* = S_{300,t}$ of the 300th firm for each year t, while keeping unchanged the corresponding idiosyncratic shocks. Such benchmark quantifies the contribution of the granular residual to the GDP fluctuations of an economy composed of equal size firms (or a representative firm). Within the representative firm framework, the contribution of the firm-level idiosyncratic shocks to aggregate fluctuations is, indeed, marginal.

The comparison of the equal weight benchmark to the granular curve gives a clear indication of the relevant role played by the very large firms in the characterization of business cycle fluctuations. Our results indicate that the heterogeneity of firms cannot be dismissed when modelling aggregate fluctuations. As a further evidence of the importance of the heterogeneity of firms, Figure 3 shows the transition from the granular curve to the equal weight benchmark curve, when we progressively remove the L largest firms in Γ_t. We replace the L largest firms with smaller size firms, ranging from the position $Q + 1$ to $Q + L$ in the ranked sample. Doing so, the sample considered is always composed of $Q = 300$ firms.

The curves representing the explanatory power of the OLS regression as a function of K and for given values of L, R^2 (K, L), exhibit smoother curvatures for larger values of L, which means lower explanatory power. In particular, the curve R^2 $(K, 190)$ is almost indistinguishable from the equal weight benchmark curve, indicating that the remaining heterogeneity across firms has a negligible impact on aggregate fluctuations.

Figure 3. Explanatory power of the regression in (5) as a function of an increasing number of firms K and for different values of L, R^2 (K, L).



Note: the incremental step is $\Delta K = 10$.

We limit the variability of β_i to the interval [0, 5.5] in order to avoid that the coefficients β_i in the regression (5) increase artificially their value. The upper bound is chosen as a conservative value, averaging the estimated coefficients from Table 1 and the calibrated value of μ from (8). Without introducing the bounded interval for β_i, the coefficients can exhibit values unrealistically high (some time higher than 100), considering that β_i are proxies for the factor usage. Interestingly, when computing the granular curve, the coefficients β_i never crosses the boundaries.

To optimally calibrate the granular size of the economy, we empirically analyze the sensitivity of the R^2 (K, L) curves to increased values of L, that is, to a gradual elimination of the larger firms. Figure 4 plots the average cumulative explanatory power (the average cumulative R^2s) as a function of L:

$$C(L) = \frac{1}{Q}\sum_{K=1}^{Q} R^2(K, L). \tag{14}$$

A simple method to calibrate K^* is, therefore, to approximatively identify the interval where the $C(L)$ curve intersects the curve of the average cumulative explanatory power of the equal-weight benchmark. The highlighted point 3 in Figure 4 indicates that the granular size of the Brazilian economy is approximately $K^* = 130$ firms. This amount is smaller than that of Spain (BLANCO-ARROYO et al., 2018). This smaller number of granular firms is not unexpected because Brazil has a smaller *h* index than Spain's and it is also a larger economy. It is harder to an individual company impacts the GDP in the Brazilian case.

Figure 4. Evolution of the C(L) curve and the equal weight benchmark curve.

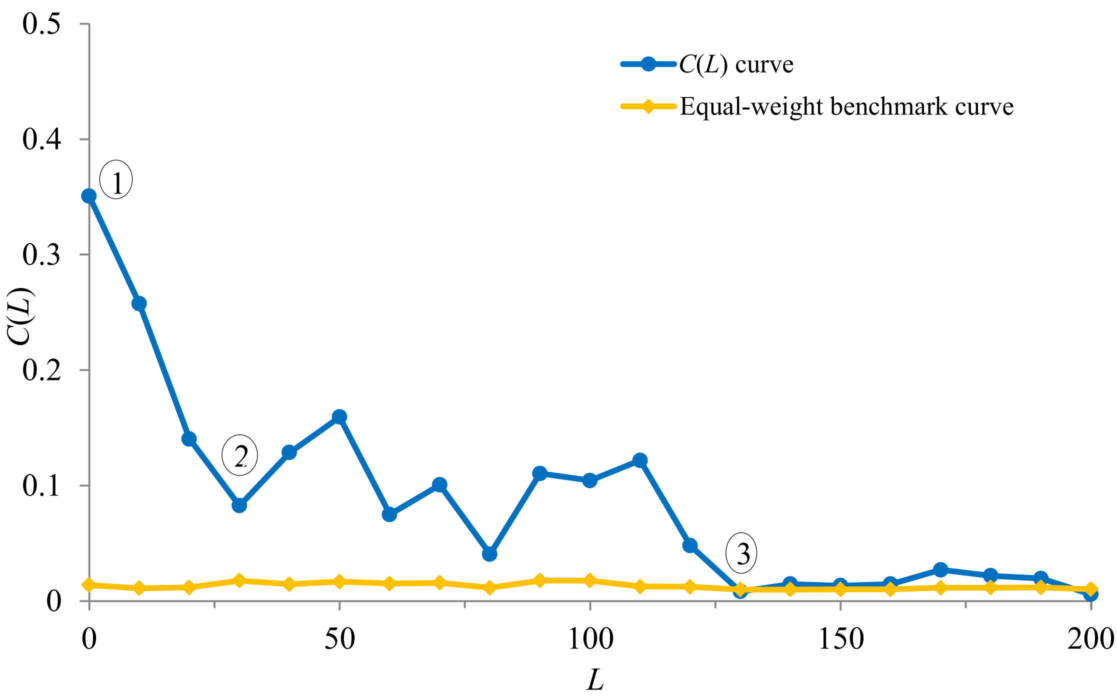


Figure 4 shows that the $C(L)$ curve decreases steadily from point 1 to point 2. Then, it exhibits a swing region, between points 2 and 3, where it hovers around 0.1. As in Blanco-Arroyo et al. (2018) we can identify within the group of granular firms an inner granular structure due to different degrees of heterogeneity across the granular firms.

Table 8 presents ordinary least squares (OLS) regressions of annual GDP growth on the simplest granular residual (1), taking into account the top 130 Brazilian companies ($K^* = 130$) over the period 1999-2018. The adjusted R^2s are higher than those presented in Table 1 (K = 100), at 37.6 per cent when we consider one lag and use Q = 100, and at 36.5 per cent when we take one lag and Q = 500. However, the results do not differ greatly from Table 1. We may conclude that Gabaix's strategy to choose the top 100 firms arbitrarily is a good fit for Brazil.

Table 8. Explanatory power of the granular residual (K* = 130 firms).

	Top 130 (Q = 130)		Top 130 (Q = 500)	
	(1)	(2)	(3)	(4)
Γ_t	3.692***	5.126***	2.640***	1.146*
	(0.748)	(0.596)	(0.712)	(0.606)
Γ_{t-1}		2.680***		3.012***
		(0.939)		(0.716)
(Intercept)	0.015***	0.050***	0.044***	0.039***
	(0.005)	(0.005)	(0.006)	(0.006)
N	19	18	19	18
R^2	0.230	0.449	0.345	0.440
Adjusted R^2	0.185	0.376	0.307	0.365

Notes: For the year t = 2000 to 2018, GDP growth is regressed on the granular residual Γ_t of the top 130 firms using (1). The firms are the largest by net revenues of the previous year. Newey-West standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

5 CONCLUSION

This research suggests that very large firms can offer a useful perspective on the Brazilian business cycle. It shows that idiosyncratic shocks to the top 100 Brazilian firms explain a large fraction of GDP fluctuations (one-third, depending on the specification). While aggregate moves such as changes to monetary, fiscal, and exchange rate policy are clearly important drivers of macroeconomic activity, they are not the only contributors to aggregate cycles.

Interestingly, the American Great Recession marks a strong break in the granularity phenomenon when considering quarterly data, with R^2s plummeting to very low levels over the period 2009-2018. The breakdown of the granular hypothesis after the end of the Great Recession is in itself an interesting and puzzling finding. Here, it could be interesting to carry out an analysis in the fashion of Dosi et al. (2019), focusing on demand-driven granular shocks to a limited number of firms. For instance, between 2010 and 2014, Petrobras, the largest Brazilian company, accounted for 8.8 per cent of total investments in the country on average (or approximately 1.8 per cent of its GDP). In the 2015, Petrobras announced a 37 per cent reduction in investments relative to the 2014-2018 period. Assuming that Petrobras' reduction in domestic goods and services occurs at the same rate of 37 per cent, there would be a 0.6 percentage point drop in GDP, without considering other indirect effects.

Our findings also support the view that an important key to explain business cycles might be found in microeconomic shocks. In addition, granular volatility may serve as an early warning system to track future GDP volatility. Therefore, tracking the performance of top firms is crucial to understand the path of the Brazilian business cycles.

Our results are in line with the empirical contributions in the literature supporting the reliability of the granular hypothesis and they contribute to strengthen the empirical relevance of the granular hypothesis. The Brazilian economy, like the U.S. economy, is populated by a large number of small and medium-size firms whose individual evolution has no impact on the aggregate level. And shocks to a small number of large companies contribute significantly to the Brazilian business cycle. Using Blanco-Arroyo et al. (2018)'s methodology, here we identify that approximately 130 granular firms play a prominent role.

The importance of idiosyncratic shocks to aggregate volatility leads to a number of implications. To better understand the origins of fluctuations, one should not focus exclusively on aggregate shocks, but on concrete shocks to the large players, such as Petrobras, Vale, or Ambev. The results in this research highlight the importance of deviating from the representative firm framework and instead consider firm-level heterogeneity in modelling of the Brazilian business cycle.

Even though this analysis provides many useful insights, there are several limitations that call for further research. One interesting line of future research is to focus on productivity shocks, as in Gabaix (2011). Here, we consider revenues as the main indicator of a company performance, due to their availability for a wide range of companies. It would be interesting to investigate how changing from revenues to productivity shocks would affect our findings. Also, it would be interesting to examine if the granular hypothesis holds for other Brazilian aggregate variables, such as exports.

REFERENCES

ACEMOGLU, Daron et al. The network origins of aggregate fluctuations. **Econometrica**, v. 80, n. 5, p.1977-2016, 2012. The Econometric Society.

ACEMOGLU, Daron; AKCIGIT, Ufuk; KERR, William. Networks and the macroeconomy: An empirical exploration. **NBER Macroeconomics Annual**, v. 30, n. 1, p.273-335, 2016.

ARROYO, Omar Blanco; ALFARANO, Simone. Granularity of the business cycle fluctuations: The Spanish case. **Economía Coyuntural, Revista de Temas de Coyuntura y Perspectivas**, v. 2, n. 1, p.31-58, 2017.

AXTELL, Robert L. Zipf distribution of US firm sizes. **Science**, v. 293, n. 5536, p. 1818-1820, 2001.

BAILY, Martin Neil. Wages and employment under uncertain demand. **The Review of Economic Studies**, v. 41, n. 1, p.37-50, 1974.

BAK, Per et al. Aggregate fluctuations from independent sectoral shocks: Self-organized criticality in a model of production and inventory dynamics. **Ricerche Economiche**, v. 47, n. 1, p.3-30, mar. 1993. Elsevier BV.

BLANCO-ARROYO, Omar et al. On the determination of the granular size of the economy. **Economics Letters**, v. 173, p.35-38, dez. 2018. Elsevier BV.

BLANK, Sven; BUCH, Claudia M.; NEUGEBAUER, Katja. Shocks at large banks and banking sector distress: The banking granular residual. **Journal of Financial Stability**, v. 5, n. 4, p. 353-373, 2009.

BRASIL. Ministério da Fazenda. Secretaria de Política Econômica (SPE). **Impactos da redução dos investimentos do setor de óleo e gás no PIB.** Nota Técnica. Brasília, DF, 2015.

CARDOSO, Ana Rute; PORTELA, Miguel. Micro foundations for wage flexibility: wage insurance at the firm level. **Scandinavian Journal of Economics**, v. 111, n. 1, p.29-50, 2009.

CARVALHO, Vasco. Aggregate fluctuations and the network structure of intersectoral trade. **Economics Working Paper**, n. 1206, p.1-58, out. 2010. Universitat Pompeu Fabra.

CARVALHO, Vasco; GABAIX, Xavier. The great diversification and its undoing. **American Economic Review**, v. 103, n. 5, p.1697-1727, ago. 2013. American Economic Association.

CLEMENTI, Gian Luca; HOPENHAYN, Hugo A. A theory of financing constraints and firm dynamics. **The Quarterly Journal of Economics**, v. 121, n. 1, p. 229-265, 2006.

COCHRANE, John H.. Shocks. **Carnegie-Rochester Conference Series On Public Policy**, v. 41, p. 295-364, 1994. North-Holland.

COSTA FILHO, Adonias Evaristo da. **Ensaios em macroeconomia aberta.** 2015. 137 f. Tese (Doutorado) - Curso de Economia, Universidade de Brasília, Brasília, 2015.

DA SILVA, Sergio et al. Granularity of the top 1,000 Brazilian companies. **Physica A**: Statistical Mechanics and its Applications, v. 512, p.68-73, dez. 2018. Elsevier BV.

DEL ROSAL, Ignacio. Power laws in EU country exports. **Empirica**, v. 45, n. 2, p. 311-337, 2018.

DEL ROSAL, Ignacio. The granular hypothesis in EU country exports. **Economics Letters**, v. 120, n. 3, p.433-436, set. 2013. Elsevier BV.

DI GIOVANNI, Julian; LEVCHENKO, Andrei A. Country size, international trade, and aggregate fluctuations in granular economies. **Journal of Political Economy**, v. 120, n. 6, p. 1083-1132, 2012.

DI GIOVANNI, Julian; LEVCHENKO, Andrei A.; MEJEAN, Isabelle. Firms, destinations, and aggregate fluctuations. **Econometrica**, v. 82, n. 4, p.1303-1340, 2014. The Econometric Society.

DOMAR, Evsey D. On the measurement of technological change. **The Economic Journal**, v. 71, n. 284, p. 709-729, 1961.

DOSI, Giovanni et al. Debunking the granular origins of aggregate fluctuations: From real business cycles back to Keynes. **Journal of Evolutionary Economics**, v. 29, n. 1, p. 67-90, 2019.

DUPOR, Bill. Aggregation and irrelevance in multi-sector models. **Journal of Monetary Economics**, v. 43, n. 2, p. 391-409, 1999.

EBEKE, Christian; EKLOU, Kodjovi M.. The granular origins of macroeconomic fluctuations in Europe. **IMF Working Paper**, n. 17/229, p.1-32, nov. 2017.

FORNARO, Paolo; LUOMARANTA, Henri. Aggregate fluctuations and the effect of large corporations: Evidence from Finnish monthly data. **Economic Modelling**, v. 70, p.245-258, abr. 2018. Elsevier BV.

FRIBERG, Richard; SANCTUARY, Mark. The contribution of firm-level shocks to aggregate fluctuations: The case of Sweden. **Economics Letters**, v. 147, p.8-11, out. 2016. Elsevier BV.

GABAIX, Xavier. The granular origins of aggregate fluctuations. **Econometrica**, v. 79, n. 3, p.733-772, 2011. The Econometric Society.

HORVATH, Michael. Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks. **Review of Economic Dynamics**, v. 1, n. 4, p.781-808, out. 1998. Elsevier BV.

HORVATH, Michael. Sectoral shocks and aggregate fluctuations. **Journal of Monetary Economics**, v. 45, n. 1, p.69-106, fev. 2000. Elsevier BV.

JONES, Charles I. Intermediate goods and weak links in the theory of economic development. **American Economic Journal: Macroeconomics**, v. 3, n. 2, p. 1-28, 2011.

KYDLAND, Finn E.; PRESCOTT, Edward C.. Time to build and aggregate fluctuations. **Econometrica**, v. 6, n. 50, p.1345-1370, nov. 1982. Econometric Society.

LONG, John B.; PLOSSER, Charles I.. Real business cycles. **Journal of Political Economy**, v. 91, n. 1, p.39-69, fev. 1983. University of Chicago Press.

LUCAS, Robert E. Jr.. Understanding business cycles. **Carnegie-Rochester Conference Series on Public Policy**, v. 1, n. 5, p.7-29, jan. 1977. Elsevier.

MANSKI, Charles F. Identification of endogenous social effects: The reflection problem. **The Review of Economic Studies**, v. 60, n. 3, p.531-542, 1993.

MIRANDA-PINTO, Jorge; SHEN, Yuanting. A granular view of the Australian business cycle. **Economic Record**, v. 95, n. 311, p.407-424, 2019.

MOURA, Guilherme V. Multiplicadores fiscais e investimento em infraestrutura. **Revista Brasileira de Economia**, v. 69, n. 1, p. 75-104, 2015.

OREIRO, José Luis. Muito além do tripé: Proposta de um novo regime de política macroeconômica para dobrar a renda per capita em 20 anos. **Indústria e desenvolvimento produtivo no Brasil**, p.121-152, 2015. Elsevier

PRESCOTT, Edward C.. Theory ahead of business-cycle measurement. **Carnegie-rochester Conference Series on Public Policy**, v. 25, p.11-44, set. 1986. Elsevier BV.

STELLA, Andrea. Firm dynamics and the origins of aggregate fluctuations. **Journal of Economic Dynamics And Control**, v. 55, p.71-88, jun. 2015. Elsevier BV.

WAGNER, Joachim. The German manufacturing sector is a granular economy. **Applied Economics Letters**, v. 19, n. 17, p.1663-1665, 2012.

APPENDIX

Table 9. Descriptive statistics for the annual database (in thousand reais/deflated to 2018 using IPCA).

Industry	1999				2008				2018			
	Number of firms	Among top 100	Average revenue	Total revenue	Number of firms	Among top 100	Average revenue	Total revenue	Number of firms	Among top 100	Average revenue	Total revenue
Agriculture	15	2	1,147,028.10	17,205,421.57	24	3	2,615,729.96	62,777,519.14	31	6	4,685,809.76	145,260,102.69
Automotive	34	7	2,415,726.81	82,134,711.47	40	15	6,678,528.66	267,141,146.31	22	9	8,009,861.33	176,216,949.34
Capital goods	6	0	982,805.37	5,896,832.23	7	0	2,234,804.12	15,643,628.84	3	0	3,114,256.84	9,342,770.52
Chemical	44	5	1,169,881.23	51,474,774.32	38	4	3,032,139.77	115,221,311.17	32	6	4,982,805.48	159,449,775.28
Construction	21	1	910,285.10	19,115,988.06	24	4	2,496,905.98	59,925,743.62	7	0	2,581,601.00	18,071,206.99
Consumer goods	67	10	1,386,133.82	92,870,966.18	57	12	4,151,423.55	236,631,142.09	37	11	9,340,064.96	345,582,403.69
Electronics	23	5	1,489,192.07	34,251,417.64	21	3	2,487,219.75	52,231,614.78	12	2	4,635,859.80	55,630,317.61
Healthcare	3	1	1,263,434.74	3,790,304.22	13	0	1,999,430.80	25,992,600.44	32	2	3,250,234.91	104,007,517.22
Information	7	2	1,520,465.79	10,643,260.51	2	1	5,815,854.82	11,631,709.64	2	1	6,013,728.35	12,027,456.70
Infrastructure	14	3	1,354,911.15	18,968,756.10	9	1	3,224,475.34	29,020,278.02	14	1	3,820,847.56	53,491,865.86
Iron and steel	27	4	1,382,279.83	37,321,558.12	32	7	4,478,144.71	143,300,630.70	21	8	6,687,732.28	140,442,377.86
Mining	11	2	1,775,462.86	19,530,091.48	12	2	6,359,732.41	76,316,788.92	13	2	9,184,084.94	119,393,104.21
Oil and Energy	43	15	3,352,161.46	144,142,942.64	58	13	7,673,945.24	445,088,824.19	92	15	7,294,278.15	671,073,589.66
Other	0	0	-	-	3	0	1,052,102.88	3,156,308.64	3	0	2,367,112.74	7,101,338.21
Pharmaceutical	11	1	949,349.73	10,443,342.01	11	0	1,647,127.56	18,118,403.21	9	0	3,095,151.06	27,856,359.55
Pulp and paper	14	1	1,045,971.95	14,643,607.34	11	2	2,679,473.51	29,474,208.64	6	3	7,273,159.11	43,638,954.68
Retail	40	9	1,832,463.56	73,298,542.21	39	6	4,381,628.51	170,883,512.08	44	11	6,123,704.77	269,443,009.92
Service	11	2	1,579,324.44	17,372,568.86	14	1	3,113,926.87	43,594,976.23	16	2	4,185,336.40	66,965,382.42
Technology	17	3	1,429,722.10	24,305,275.65	9	2	2,568,528.18	23,116,753.58	11	0	2,252,892.56	24,781,818.12
Telecommunications	31	10	1,998,756.81	61,961,461.23	16	10	9,659,769.40	154,556,310.43	8	4	12,454,662.60	99,637,300.79
Textile and apparel	11	0	774,070.16	8,514,771.77	5	0	1,752,250.17	8,761,250.86	4	0	2,341,369.21	9,365,476.85
Transportation	16	3	1,673,610.49	26,777,767.81	18	3	3,656,938.47	65,824,892.39	21	3	3,823,668.88	80,297,046.42
Wholesale	34	14	3,099,252.79	105,374,594.78	37	11	7,661,575.32	283,478,286.80	60	14	8,336,405.07	500,184,304.33
Total	500	100	34,532,290.36	880,038,956.20	500	100	91,421,655.98	2,341,887,840.72	500	100	125,854,627.76	3,139,260,428.92

Source: *Exame* magazine.

Table 10. Descriptive statistics for the quarterly database (in thousand reais/deflated to 2018 using IPCA).

Industry	1997Q1				2008Q1				2018Q4			
	Number of firms	Among top 100	Average revenue	Total revenue	Number of firms	Among top 100	Average revenue	Total revenue	Number of firms	Among top 100	Average revenue	Total revenue
Agriculture	0	0	-	-	6	0	50,261.71	301,570.25	11	3	550,993.55	6,060,929.00
Automotive	13	12	194,986.50	2,534,824.56	24	6	240,279.58	5,766,710.00	25	5	635,773.00	15,894,325.00
Capital goods	4	4	156,139.39	624,557.58	4	1	325,893.25	1,303,573.00	6	1	656,307.83	3,937,847.00
Chemical	4	4	349,838.16	1,399,352.64	7	2	780,349.43	5,462,446.00	7	1	2,409,111.14	16,863,778.00
Construction	7	6	73,608.78	515,261.46	28	2	98,742.90	2,764,801.26	32	2	199,616.24	6,387,719.65
Consumer goods	3	3	1,318,311.13	3,954,933.38	8	6	1,913,338.88	15,306,711.00	7	5	11,989,010.00	83,923,070.00
Electronics	1	1	1,668,771.84	1,668,771.84	2	1	601,317.50	1,202,635.00	2	1	806,064.50	1,612,129.00
Healthcare	1	1	123,924.16	123,924.16	7	2	524,522.43	3,671,657.00	14	5	1,459,102.36	20,427,433.00
Information	0	0	-	-	0	0	-	-	0	0	-	-
Infrastructure	2	2	1,292,583.91	2,585,167.82	11	4	336,183.10	3,698,014.09	16	4	766,679.38	12,266,870.00
Iron and steel	12	12	599,133.69	7,189,604.31	15	3	1,095,747.53	25,380,723.00	14	3	1,549,328.04	21,690,592.61
Mining	2	2	1,384,889.84	2,769,779.69	4	1	3,602,749.25	16,436,213.00	3	1	12,534,632.33	37,603,897.00
Oil and Energy	19	19	1,612,885.20	30,664,818.74	54	36	1,633,230.74	88,194,460.00	78	30	2,411,830.64	188,122,790.00
Other	5	4	100,960.07	504,800.35	7	0	98,004.86	686,034.00	7	0	212,019.14	1,484,134.00
Pharmaceutical	0	0	-	-	0	0	-	-	5	1	453,548.16	2,267,740.79
Pulp and paper	4	4	532,090.95	2,128,363.79	6	3	466,766.83	2,800,601.00	7	4	1,676,842.43	11,737,897.00
Retail	9	8	860,293.77	7,742,643.90	13	7	708,497.05	9,210,461.61	17	7	3,269,106.67	55,574,813.41
Service	0	0	-	-	42	7	201,929.33	8,481,032.00	102	7	236,590.71	24,132,252.88
Technology	2	2	728,237.55	1,456,475.10	3	2	292,407.33	877,222.00	8	0	186,308.29	1,490,466.33
Telecommunications	2	2	2,207,711.13	4,415,422.25	4	4	2,475,238.75	9,900,955.00	7	4	4,255,480.57	29,788,364.00
Textile and apparel	14	13	98,506.41	1,379,089.77	20	5	173,798.56	3,475,971.28	17	2	380,854.92	6,474,533.56
Transportation	2	1	42,441.03	84,882.07	29	4	193,600.57	5,614,416.43	63	8	445,536.06	28,068,772.00
Wholesale	0	0	-	-	5	4	1,599,880.40	7,999,402.00	7	6	8,330,477.86	58,313,345.00
Total	106	100	13,345,313.51	71,742,673.41	299	100	17,412,739.99	218,535,608.91	455	100	55,415,213.82	634,123,699.22

Source: Economática.

Table 11. Unit root tests for the annual time series (Augmented Dickey-Fuller and Phillips-Perron).

Variable	ADF		PP	
	t-statistic	prob.	Adj. t-statistic	prob.
GDP growth	-2.1918	0.0309**	-2.1095	0.0398**
Granular residual, Q = 100	-2.7151	0.0097***	-2.6793	0.0105**
Granular residual, Q = 130	-2.9044	0.0062***	-2.8795	0.0066***
Granular residual, Q = 500	-1.9232	0.0540*	-1.9232	0.0540*
Industry demeaned granular residual	-2.2215	0.0290**	-2.1327	0.0350**

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

Table 12. Unit root tests for the quarterly time series (Augmented Dickey-Fuller and Phillips-Perron).

Variable	ADF		PP	
	t-statistic	prob.	Adj. t-statistic	prob.
GDP growth	-7.9085	0.0000***	-11.5681	0.0000***
Granular residual	-1.7329	0.0788*	-8.6920	0.0000***
Industry demeaned granular residual	-2.1291	0.0327**	-9.7088	0.0000***

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 13. Jarque Bera test (normality of the residuals).

Equation	prob.
Table 1 (1)	0.1849
Table 1 (2)	0.9442
Table 1 (3)	0.4844
Table 1 (4)	0.2657
Table 2 (1)	0.9583
Table 2 (2)	0.9966
Table 3 (1)	0.5786
Table 3 (2)	0.6031
Table 4 (1)	0.1546
Table 4 (2)	0.2097
Table 5 (1)	0.1010
Table 5 (2)	0.1236
Table 5 (3)	0.1144
Table 5 (4)	0.1678
Table 5 (5)	0.3982
Table 6 (1)	0.1765
Table 6 (2)	0.2273
Table 6 (3)	0.2022
Table 8 (1)	0.8427
Table 8 (2)	0.9605
Table 8 (3)	0.3171
Table 8 (4)	0.3210