Big Fish in a Small Pond: Locally Dominant Firms and the Business Cycle*

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Abstract

Following Gabaix (2011), we identify locally dominant firms that have a strong impact on their local macroeconomic environment, but are not among the largest 100 U.S. firms. Idiosyncratic shocks to these locally dominant firms also propagate nationally and explain a significant portion of aggregate U.S. macroeconomic fluctuations. Specifically, we find that locally dominant firms exist in 13 U.S. states and productivity shocks to these firms explain almost 50% of the U.S. GDP growth.

Keywords: Idiosyncratic shocks; state-level business cycle; U.S. business cycle; economic contagion.

JEL classification: B22, E30, E32.

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Abstract

Following Gabaix (2011), we identify locally dominant firms that have a strong impact on their local macroeconomic environment, but are not among the largest 100 U.S. firms. Idiosyncratic shocks to these locally dominant firms also propagate nationally and explain a significant portion of aggregate U.S. macroeconomic fluctuations. Specifically, we find that locally dominant firms exist in 13 U.S. states and productivity shocks to these firms explain almost 50% of the U.S. GDP growth.

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1 Introduction

In a recent study, Gabaix (2011) demonstrates that idiosyncratic productivity shocks to the 100 largest U.S. firms account for almost 30% of the U.S. GDP growth. Relative to other economy-wide shocks, such as monetary shocks, the aggregate impact of these "large" firms on the U.S. economy is economically significant. In this study, we extend Gabaix's (2011) insight and examine whether a similar firm-induced economic mechanism could drive state-level business cycles. We also study whether the impact of large local firms on the local economies aggregate and affect the growth of the overall U.S. economy.

Our key insight is that there exist "locally dominant" firms that may not be very large at the national level but they may play a significant role in the growth of the local or the regional economy, i.e., these firms may act like a "big fish in a small pond." Productivity shocks to these locally dominant firms could first affect the local/regional economy. Subsequently, the impact of these locally dominant firms could spread to other U.S. states and could even aggregate and affect the U.S. business cycle. This hypothesis is motivated by prior studies, which demonstrate that the U.S. economy is better described as a collection of 50 state-level economies as opposed to one fully integrated national economy (e.g., Asdrubali et al., 1996; Athanasoulis and Wincoop, 2001; Korniotis, 2008; Korniotis and Kumar, 2013; Addoum et al., 2017; Bernile et al., 2020.[1]

We study the significance of locally dominant firms by focusing on two main research questions. First, we determine whether productivity shocks to certain large, local firms affect the growth of their local economy. Second, we investigate whether shocks to these locally dominant firms are systematic at the national level and explain the aggregate/national business cycle. Moreover, we examine whether the impact of locally dominant firms on the U.S. business cycle is significant and comparable to the aggregate effect of very large firms identified by Gabaix (2011).

[1]In particular, these studies show that accounting for the heterogeneity across the U.S. states improves the performance of asset pricing models in explaining the cross-sectional variation in stock returns (see Korniotis, 2008).

For our first research question, we follow Gabaix (2011) to identify locally dominant firms at the state level.[2] In doing so, we rank firms in each state based on their sales on an annual basis and classify those with sales in the top quartile of the sales distribution as locally dominant firms. To ensure that our results are not driven by the known impact of very large national companies on the U.S. economy, we exclude the top-100 U.S. firms from our sample of locally dominant firms. We further confirm that our results are not sensitive to the top quartile cut off and that the composition of locally dominant firms is persistent across time.

Subsequently, we measure firm-specific shocks to the locally dominant firms over the 1977 to 2017 period. Like Gabaix (2011), we measure a firm's productivity growth as the annual log change in its net sales per employee. From the productivity growth, we subtract the average productivity growth of all firms in the same headquarter (HQ) state and use this difference as our measure of firm-level shocks. We then take a weighted average (based on firm sales) of the idiosyncratic shocks of all the locally dominant firms in each state to measure the granular residual in that state. The granular residual and its lagged value are the two main independent variables in our regressions where the dependent variable is state-level GDP growth. The goal of our regressions is to identify the portion of the variation in the local GDP growth captured by the current and lagged values of shocks to locally dominant firms.

Based on the estimated R^2 from the state-level regressions, we divide the U.S. states into two groups: "granular" and "non-granular" states. Granular states are those states in which shocks to locally dominant firms explain a large portion of the state's GDP growth. We identify 13 granular states: California, Vermont, Florida, Mississippi, Alabama, Arizona, Wisconsin, Indiana, Oklahoma, New Jersey, Nevada, New Mexico, and Texas. In the case of California, for example, shocks to locally dominant firms explain over 28% of the state's GDP growth. In economic terms, a one-standard-deviation increase in shocks to locally

[2] Our decision to set the local economy at the state level is guided by the fact that at the regional level, state-level data are available for the longest period. However, our main conclusion remains the same when we use the metropolitan statistical area (MSA) data that are available for a much shorter period than the state-level data.

dominant firms in California is associated with a 37-percentage-points (pps) increase in California's GDP growth. This is a meaningful effect, given that the average GDP growth of California is 1.6% per year.[3]

Next, we investigate possible theoretical reasons for why some states are granular while others are not. In doing so, we examine whether the theoretical prediction of prior studies (e.g., Gabaix, 2011; Acemoglu et al., 2012) explains the granularity of local economies. Specifically, Gabaix (2011) suggests that the heavy right-skewness in the distribution of the U.S. firm size drives the granularity of the national economy. Acemoglu et al. (2012) further show that the granularity of an economy depends on the structure of the connections among firms. Therefore, we expect granular states to either have a heavy right-skewness in the distribution of local firm size or have a firm network with the properties suggested in Acemoglu et al. (2012).

To empirically test the above theories, we first identify states in which firm size has a power-law distribution (i.e., states with a fat-tailed distribution). We find that 11 states have a fat-tailed firm size distribution. They are California, Texas, Minnesota, Wisconsin, Illinois, Ohio, Pennsylvania, New Jersey, New York, North Carolina, and Florida. Among these 11 states, 5 are granular (California, Texas, Wisconsin, New Jersey, and Florida). This evidence confirms that, for some states, the heavy right-skewness of firm size distribution drives the granularity.

A puzzling finding of our analysis is that there are U.S. states that are not granular, but still have a fat-tailed firm size distribution. This result suggests that the fat-tailed distribution of firm size is not a *sufficient* condition to empirically identify a granular economy. One explanation for this finding is the "size-variance" relationship. In particular, because large firms are less volatile than small firms, the granular forces may be absent even in the presence of a fat-tailed firm size distribution (Yeh, 2018). We offer a second explanation. Specifically, we conjecture that in addition to a heavy right-skewness, firm size distribution needs to have a small tail decay rate to be empirically identified as granular. When the tail

[3]This effect is 22% in Vermont, 21% in Florida, 18% in Mississippi, 16% in Alabama and Arizona, 13% in Wisconsin and Indiana, 12% in Oklahoma and New Jersey, 11% in Nevada, 10% in New Mexico, and 9% in Texas.

decay rate is small, extreme occurrences (i.e., shocks to large firms) dissipate at a slower rate and subsequently may lead to an aggregate effect that can be traced empirically.

We find that the tail decay rate of firm size distribution is indeed an important determinant of granularity. Specifically, we find a negative and statistically significant correlation of 73% between the tail decay rate of firm size distribution and the economic power of locally dominant firms in explaining the local business cycles. That is, among the 11 states with a fat-tailed distribution of firm size, the smallest tail decay rates belong to states with a granular economy. These states are California, Texas, Wisconsin, New Jersey, and Florida.

Subsequently, we investigate the effects of firms' networks on local granularity. To proxy for firms' connections, we use co-movements of non-dominant firms' excess returns with those of locally dominant firms in the same state. Our findings indicate that, among states in which firm size distribution is not heavy right-skewed, a larger return co-movement is positively correlated with granularity effect. We further find that a higher exposure of non-dominant firms' fundamental values to those of locally dominant firms is positively correlated with granularity effect. This evidence suggests that, in addition to fat-tailed size distribution, firms' networks affect local granularity.

Proceeding to our second research question, we study whether shocks to locally dominant firms in the granular states *propagate* to other states' economies. In other words, we rotate the baseline regressions in the sense that the independent variables are the granular residual of granular states, and the dependent variable is the GDP growth of the states that share a border with the granular states. We also use a similar regression to study the impact of locally dominant firms on the aggregate U.S. economic growth; that is, we use U.S. GDP growth as our dependent variable.

We find that shocks to locally dominant firms in 11 out of the 13 granular states are a significant determinant of the economic growth in neighboring states. For example, shocks to locally dominant firms in California explain over 30% of the combined GDP growth of the states that share a border with California.[4] These results indicate that local economic shocks can propagate geographically across states.

To examine the impact of local shocks on the U.S. economy, we aggregate the idiosyncratic shocks across the granular states and examine their influence on U.S. GDP growth. Given our preceding findings, we expect local shocks in the granular states to also influence the overall U.S. economy. Confirming this conjecture, we find that shocks to locally dominant firms in the granular states explain 48% of the U.S. aggregate fluctuations. This impact is comparable to the aggregate effects of the top-100 U.S. firms documented by Gabaix (2011).

Finally, we analyze whether accounting for the states' level of *granularity* strengthens the significance of locally dominant firms on the aggregate economy. In particular, instead of using an unweighted average of shocks across the granular states, we use the estimated R^2 from the baseline time-series regressions to create aggregation weights. We use these weights and measure a weighted average of shocks to locally dominant firms in the granular states and re-estimate our regressions with the U.S. GDP growth as the dependent variable. We find that accounting for state granularity increases the aggregate impact of locally dominant firms from 48% to 54%. We also confirm that our weighting method does not overestimate the effects of a few states with a larger number of dominant firms. Specifically, we find a consistent outcome when we drop granular states with the highest agglomeration of locally dominant firms (i.e., California, Florida, Texas, and New Jersey).

Overall, our results suggest that productivity shocks to firms, which are large in their geographic areas, have a considerable impact on their regional economies. Moreover, the aggregate impact of these large firms on the U.S. economy is comparable to the effect of nationally large firms. For robustness, we show our results remain similar when we use total factor productivity (TFP) to measure firms' productivity growth. Further, we account for firms' heterogeneous response to economy-wide shocks and measure a firm's productivity

[4] We also extend these regional economies to examine the economic effects of locally dominant firms on their geographic divisions. Our results show that shocks to locally dominant firms in 11 granular states explain significant portions of GDP growth across divisions. For example, shocks to locally dominant firms in OK, explain 14% of the West South Central's economic growth.

shocks as the residual of the firm's productivity growth, over and above the firm's exposure to the average productivity growth of its sector, and geographical area. We find that, among the identified granular states, productivity shocks to locally dominant firms in California, Vermont, Mississippi, Indiana, Oklahoma, New Jersey, and Texas remain an important determinant of the local economic growth. We further confirm that our results are not driven by the impact of large productivity shocks to locally dominant firms. Our results also stay consistent when we consider only the 100 largest locally dominant firms, or when we account for the economic importance of locally dominant firms in their HQ states. Finally, we confirm the robustness of our estimates, using an extended sample period of 1963 to 2017.

These findings contribute to several strands of economics and finance literature. A growing literature in macro-finance suggests that idiosyncratic shocks to individual firms can affect the overall economy (Gabaix, 2011; Acemoglu et al., 2012; Kelly et al., 2013; di Giovanni et al., 2014; Dosi et al., 2019; Miranda-Pinto and Shen, 2019). Previous studies have shown the influence of sectoral shocks in generating aggregate economic functions (e.g., Foerster et al., 2011; Atalay, 2017; Baqaee, 2018). For instance, Bigio and La'O (2016) study the aggregate influence of sectoral distortions in an input-output production network and show that through a decline in total factor productivity and through the labor wedge scrotal shocks may create macroeconomic effects. We extend this literature and show that shocks to firms that are large in their local areas but not at the national level, can affect the aggregate economy.

We also build upon the early work of Jovanovic (1987), Durlauf (1993), Bak et al. (1993), and Nirei (2006), which suggests that firm-level idiosyncratic shocks can cause aggregate fluctuations. Our paper complements these findings by providing empirical evidence that shocks to individual firms can have aggregate effects on the local and the national economy. That is, we provide an additional micro-level explanation for the U.S. business cycle (Cochrane, 1994; Christiano et al., 1998; Temin, 1998). Lastly, our work contributes to the literature on the importance of firm geography on the distribution of information (Garcia and Norli, 2012; Bernile et al., 2020). Many papers examine the information content that can be extracted from geographical locations of firms (e.g., Coval and Moskowitz, 1999, 2001;

Grinblatt and Keloharju, 2001; Ivkovic and Weisbenner, 2005). Our finding that the overall effects of locally large firms are comparable to those of nationally large companies provides supporting evidence for the importance of local economies. Overall, these results provide a useful source of information for corporations and market participants. For instance, information about the micro-origin of the local business cycle provides a better understanding of the source of local financial risk, which can influence corporate policies.

2 Data and Methods

In this section, we describe the data sets we use in our empirical analysis. We also summarize our main variables and describe our method for identifying firm-specific shocks.

2.1 State-Level GDP Growth

The primary dependent variable in our analysis is state-level GDP growth. We use the U.S. states as our geographical unit because, compared to other units such as MSAs or counties, state-level macroeconomic data are available for a longer period. For example, GDP data at the MSA level are available only since 2001. Despite the data limitation, in unreported results, we repeat our analysis at the MSA level and find similar effects.

We collect annual real GDP per capita (both at the national- and state-level) from the Bureau of Economic Analysis (BEA). Our sample period is from 1977 to 2017.[5] We collect a) the real chained GDP in 2009 dollars from 1997 to 2017 and b) the real chained GDP in 1997 dollars from 1977 to 1997. To merge these two samples, we use changes in quantity indices to extend the state GDP series in 1997 U.S. dollars backward. We then convert the pre-1997 real chained GDP series from 1997 to 2009 dollars by using the ratio of 2009-dollars GDP in 1997 to the 1997-dollars GDP in 1997 since in 1997 both series are available.

[5] Our sample starts in 1977 because the inflation information per state is not available prior to this date. As a robustness check, we use nominal GDP per capita to measure the economic growth and extend our database back to 1963 and find a consistent outcome. In this case, we complement our data with the population data from the Federal Reserve Bank of St. Louis (FRED) to measure nominal GDP per capita.

Following Biswas et al. (2017), we calculate state GDP growth as the annual log change in the real GDP per capita. That is:

$$GDP\ Growth_{j,t} = log(GDP_{j,t}) - log(GDP_{j,t-1}). \quad (1)$$

2.2 Firm-Level Data

We also use firm-level data from the Fundamental Annual section of the Compustat North America. Specifically, we obtain firms' net sales and the number of employees for the period from 1977 to 2017.[6] We exclude companies that are not located in the United States. Following Gabaix (2011), we also filter out energy companies (SIC codes between 4900 and 4940) because the sales of these firms are mostly affected by worldwide commodity prices rather than productivity shocks. We further exclude financial firms (SIC codes between 6000 and 6999) because the revenues of these firms are not a proper measure of their productivity.

2.3 Measurement of Locally Dominant Firms

We classify locally dominant firms as those firms that are the largest in their HQ state based on annual sales. That is, in each state and year, locally dominant firms are firms with sales that are in the top quartile of the firm net sales distribution from last year. Although our main findings are not sensitive to the quartile cutoff, we use this cut off to have enough locally dominant firms per state. Further, choosing locally dominant firms based on the size distribution, as opposed to fixing a specific number of firms per state, assures that we are not overestimating (or underestimating) economic effects of firms in states with a small (or large) number of companies.[7] Finally, to ensure that our results are not driven by the economic effects of nationally large firms, as documented in Gabaix (2011), we drop the top-100 largest firms in the U.S. from the sample of locally dominant firms.

[6]Compustat defines firms' net sales as the gross sales reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.

[7]To illustrate the idea, assume that there are 100 and 10 firms in states X and Y, respectively. If we focus on the economic effects of the 5 largest firms in each state, we give a higher weight to locally dominant firms in state Y. To avoid this issue, we use firm size distribution to identify locally dominant firms.

2.4 Identification of Productivity Shocks

We follow Gabaix (2011) to compute idiosyncratic productivity shocks to the locally dominant firms. In particular, we first measure a firm's productivity growth as the annual log change in the firm's net sales per employee. Specifically:

$$g_{i,j,t} = z_{i,j,t} - z_{i,j,t-1}. \tag{2}$$

Above, $z_{i,j,t} = ln(\frac{Sales_{i,j,t}}{Employees_{i,j,t}})$, where $Sales_{i,j,t}$ is the net sales of firm i, headquartered in state j, at time t, and $Employees_{i,j,t}$ is the firm's total number of employees.

Next, we subtract from the firm's productivity growth the average productivity growth of all companies that are headquartered in state j. That is, we measure idiosyncratic shocks as:

$$\xi_{i,j,t} = g_{i,j,t} - K^{-1} \sum_{i=1}^{K} g_{i,j,t}, \tag{3}$$

where, K is the total number of firms headquartered in state j at time t. By subtracting the average productivity growth, we can isolate the component of sales that is specific to the firm.

Finally, for each state, we compute a weighted average of shocks to all locally dominant firms. We denote this measure by Γ, which takes the following form for state j in year t:

$$\Gamma_{j,t} = \sum_{i=1}^{L_j} \frac{S_{i,j,t-1}}{Y_{j,t-1}} \hat{\xi_{i,j,t}}. \tag{4}$$

Above, L_j is the total number of locally dominant firms in state j, and $Y_{j,t-1}$ is the state's GDP at time $t-1$. Consistent with Gabaix's (2011) terminology, we refer to $\Gamma_{j,t}$ as the *"granular residual."* This granular residual is our main variable of interest and our goal is to examine the economic impact of $\Gamma_{j,t}$ on the state economic fluctuations.

2.5 Summary Statistics

We report the summary statistics of our main variables in Table 1. Specifically, Table 1 shows the net sales, number of employees, productivity growth, granular residual, annual number of firms, and GDP growth in each state throughout the sample period.

As shown in Table 1, the average revenues of firms range from \$71.41 million (in New Mexico) to \$13 billion (in Arkansas). Further, firms' average number of employees ranges from 441 (in North Dakota) to 72,843 (in Arkansas). Firms' annual productivity growth ranges from 2% (in Alaska) to 6% (in Montana). California, with an average of 618, has the largest number of firms per year. Finally, the annual average of states' GDP growth ranges from 0.4% (in Nevada) to 2.7% (in Oregon).

In Table A1, we show the Pearson correlation between states' GDP growth and the granular residual measure from Equation (4). Panel A of Table A1 shows a positive correlation of 4.6% between Γ_t and state GDP growth. This correlation is statistically significant at the 5% confidence level and suggests that shocks to locally dominant firms are related to the economic condition in their HQ states. We further investigate this evidence in the following section.

3 Which States Are Granular?

We begin our main empirical analysis by separating U.S. states into two categories: (1) granular states, that is, states whose economies are affected by the productivity shocks of the locally dominant firms, and (2) non-granular states.

3.1 Identification of Granular States

Our goal in this section is to determine whether shocks to locally dominant firms explain the economic growth of their HQ states. To this end, we regress a state's GDP growth on the current and lagged value of its granular residual from Equation (4). Specifically:

$$GDP\ Growth_{j,t} = \alpha + \beta_1 \Gamma_{j,t} + \beta_2 \Gamma_{j,t-1} + \varepsilon_{j,t}, \tag{5}$$

From the above regression, we are interested in the estimated R^2, which shows the statistical power of $\Gamma_{j,t}$ and $\Gamma_{j,t-1}$ in explaining the state's business cycles. Based on the results, we classify "*granular states*" as states for which the estimated R^2 from the above regression is above 8%. We choose this criterion because the estimated R^2 for other states is very small (on average, around 2%). However, to gain a full overview of the sample, we report the estimated R^2 for all states in Figure C5.

We find that there are 13 states for which the granular residuals of the locally dominant firms can explain a significant portion (up to 30%) of the state's GDP growth. They are California, Vermont, Florida, Mississippi, Alabama, Arizona, Wisconsin, Indiana, Oklahoma, New Jersey, Nevada, New Mexico, and Texas. We report the estimation results of Regression (5) for these granular states in Table 2.

The results show that the granular residuals of locally dominant firms in California significantly affect the state's GDP growth ($\Gamma_{j,t} = 0.387$, t-statistic = 3.52; $\Gamma_{j,t-1} = 0.359$, t-statistic = 3.47). Further, shocks to locally dominant firms in California explain 28.5% of the state's GDP growth. The predictive power of $\Gamma_{j,t}$ and $\Gamma_{j,t-1}$ is also economically meaningful in other granular states. The explanatory power of these variables ranges from 21.7% in Vermont to 8.7% in Texas. The strong economic significance of the granular residual is also consistent with the correlation coefficients, reported in Panel B of Table A1. Specifically, when we focus on the sample of granular states, the Pearson correlation between $\Gamma_{j,t}$ and state-level GDP growth increases to 17.2%, as opposed to a correlation of 4.6% when we consider all states in our sample.

In Figure 1, we show the geographic distribution of the granular states. In the figure, states, where the locally dominant firms have higher economic effects (based on the estimated R^2), are shown in a darker shade. From the geographic distribution of granular states, we see that, in addition to large and economically important states, such as California and Texas, (Bernile et al., 2020) smaller states, such as Vermont and New Jersey, also have a granular economy.

The impact of firm shocks in the granular states is economically significant too. To facilitate the comparison of economic magnitude across different states, the regressions coefficients in Table 2 are reported in standardized form; that is, our variables have a mean equal to 0 and a standard deviation equal to 1. Based on these standardized coefficient estimates we find that a one-standard-deviation increase in the granular residual of locally dominant firms in a large state like California is associated with a 37-pps increase in the standard deviation of the state's economic growth. Compared to the average of 1.6% growth in California's GDP from 1977 to 2017, this is a considerable economic effect. The effect of firm-level shocks is also economically significant in other granular states. In particular, the economic magnitude of the effect ranges from 30 pps in New Jersey to 11 pps in Indiana.

3.1.1 Characteristics of Locally Dominant Firms

In this section, we take a closer look at the sample of locally dominant firms in the granular states. Our classification of granular states relies on a statistical measure (i.e., R^2). Therefore, to ensure that this statistical identification is economically intuitive, we report various characteristics of the locally dominant firms and compare them with the characteristics of other local firms in Table 3.

In Panels A and B of Table 3, we report the average number of locally dominant and non-dominant firms along with their net sales and number of employees. By construction, the average number of locally dominant firms in granular states is one-third of non-dominant companies. However, the sales and number of employees of locally dominant firms, on average, are ten times larger compared to those of non-dominant firms. For example, while there are only 16 locally dominant firms in AZ (compared to 44 non-dominant firms), the average net sales of these firms are $2.5 billion, whereas the average net sales of the non-dominant firms are only $164 million.

In Table A2, we further report a snapshot of locally dominant firms. As we expect, among the reported firms, there are important companies. For example, "Sanderson Farms" is a locally dominant firm headquartered in Mississippi, which is one of the nation's largest poultry producers. "Vulcan Material Company," headquartered in Alabama, is one of the largest producers of construction materials. Although these firms are large in their local areas, they are considerably smaller than nationally large firms (see Panel B of Table A2). Collectively, the evidence in Table 3 and Table A2 confirm that we have identified firms that are indeed important local firms.

3.1.2 Does Sample of Locally Dominant Firms Change Frequently?

One potential concern with our analysis is that our classification of locally dominant firms might not be persistent. In other words, the identification could be a random classification. To address this issue, we conduct the Wald–Wolfowitz (1968) Run's test.

Specifically, we identify firms that, at some point throughout the sample, are designated as locally dominant. Next, we define an indicator variable equal to 1 if the company is a locally dominant firm in a specific year, and 0 otherwise. In this way, for each locally dominant firm, we create a sequence of ones and zeros, where ones declare times that the firm is locally dominant.

We denote the total number of ones in firm i's sequence as n_1, and the total number of zeros as n_2. Then, we perform the Run's test by computing the following z score:

$$z_i = \frac{R - \bar{R}}{s_R}, \tag{6}$$

where R shows the number of times that the sequence switches between 1 and 0. We compute $\bar{R}$ and ${s_R}^2$ as:

$$\bar{R} = \frac{2n_1n_2}{n_1+n_2} + 1, \tag{7}$$

$${s_R}^2 = \frac{2n_1n_2\ (2n_1n_2 - n_1 - n_2)}{(n_1+n_2)^2\ (n_1+n_2-1)}. \tag{8}$$

Using the above measure, we test the null hypothesis, that the sequence of ones and zeros is produced randomly .[8] Table 4 shows the Run's test result for each granular state. The results indicate that, at the 5% confidence level, more than 90% of the locally dominant firms have a non-random sequence of presence in the sample. This result suggests that our classification of locally dominant firms is stable and not noisy.

3.2 Theoretical Mechanisms for Granularity at the Local Level

In our baseline analysis in Section 3.1, we identified 13 granular states and showed that productivity shocks to locally dominant firms in these states affect local economic fluctuations. In this section, we examine theoretical reasons for why some states are granular while others are not. On the one hand, Gabaix (2011) shows if the size distribution of firms in an economy has a heavy right-skewness, idiosyncratic shocks to the largest firms do not average out and affect the macroeconomy. On the other hand, Acemoglu et al. (2012) note that the granularity of an economy also depends on how firms are connected via their networks. They show that if some firms have disproportionately more connections than others, shocks to these highly connected firms may propagate to the overall economy.

To empirically test these theoretical conjectures, we first identify states with a fat-tailed distribution of firm size. To do so, we follow Axtell (2001) and fit a power-law distribution to firm size data in each state.[9] Like in Axtell (2001), for the analysis of this section, we

[8]Specifically, we reject the null hypothesis if the absolute value of the z-score in Equation (6) is greater than 1.96.

[9]Although other distributions have also been used in the literature to identify fat-tailed distributions, such as log-normal, and student's t, we focus on power-law distribution to be consistent with Gabaix's (2011) methodology.

use the number of employees to measure a firm's size. Given that firms' revenues and the number of employees are highly correlated, this choice does not affect the properties of the estimated distribution (see Axtell, 2001). Specifically, we obtain firm size information from the U.S. Small Business Administration (SBA). As Axtell (2001) argues, Compustat does not provide information on privately held firms, and ignoring these firms may result in an inaccurate estimation of firm size distribution. Therefore, we use the SBA database to obtain the size information for public and private firms. However, to be consistent with our baseline analysis, we also investigate states' firm size distribution using only Compustat data.[10]

In Table B1 we show a cross-sectional example of the data for two (random) states: Florida and Ohio. For each state, SBA categorizes firms into different size classes based on the number of employees and reports the total number of firms within each class. With the SBA data, we estimate the tail exponent of each state size distribution. The tail exponent identifies whether the distribution has a heavy right-skewness (i.e., if the distribution is fat-tailed). We obtain this tail exponent using the following cumulative function of a power-law distribution:

$$Pr(S \geq s) = (\frac{s_0}{s})^{\alpha}, s \geq s_0. \tag{9}$$

Above, s_0 is the minimum size. The parameter α is the tail exponent, which is our main variable of interest.

To estimate α, we first transform the SBA data by taking the natural logarithms of both the size classes and the total number of firms in each class. Next, we fit a line to the transformed rank-size data and obtain the distribution's tail exponent using the slope of the fitted line. For example, in Figure B1, the fitted line yields a slope of -0.71 (Standard Error = 0.05 and Adj. $R^2 = 0.95$) for Florida, and a slope of -0.67 (Standard Error = 0.05 and Adj. $R^2 = 0.94$) for Ohio. These estimates suggest that, relative to Ohio, the firm size distribution in Florida has a heavier right-skewness.

[10] Due to the data limitation of firms observation (per year/per state) in Compustat, fitting a power-law distribution to the Compustat data is not feasible. Therefore, we fit a *Levy distribution* to the mean of firm size per state. We find that our results with Compustat data are similar to those based on the SBA database.

Using the above method, we estimate the tail exponent for each state and consider states with a tail exponent between 0.6 and 0.9 as states with a fat-tailed distribution.[11] Overall, we identify 11 states with a fat-tailed distribution of firm size. They are California, Texas, Minnesota, Wisconsin, Illinois, Ohio, Pennsylvania, New Jersey, New York, North Carolina, and Florida.

Among these 11 states, we find 5 to be granular. They are California, Texas, Wisconsin, New Jersey, and Florida. Consistent with Gabaix's (2011) prediction, this finding suggests that due to the heavy right-skewness in the firm size distribution of these 5 states, shocks to locally dominant firms do not average out and create an aggregate impact at the state level.

What remains puzzling is that, while some states like Minnesota, Ohio, New York, North Carolina, Illinois, and Pennsylvania have a fat-tailed size distribution, we didn't identify them as granular. This puzzling finding suggests that having a fat-tailed distribution might not be a sufficient condition to *empirically* identify local granularity. As explained before, the size-variance relationship might be one explanation for this finding. Because large firms have lower volatility compared with small firms, the granular forces may become absent even when the firm size distribution is fat-tailed (Yeh, 2018). In the next section, we propose a second explanation, based on the tail decay rate of firm size distribution.

3.3 Tail Decay Rate and Empirical Tests of Granularity

As mentioned in the prior section, some states have a fat-tailed size distribution but are not granular. To examine this finding, we study the role of tail decay rates of the size distributions. The tail decay rate is the rate at which the probability of an extreme occurrence converges to 0 (see Lux and Sornette (2002)). If the size distribution of a state has a fat tail

[11] Axtell (2001) estimates a tail exponent equal to 1 for the sample of U.S. firms. There are two potential reasons why we do not obtain a similar tail exponent in our state-level sample. First, Axtell (2001) uses a customized table that has disaggregated information about larger size class bins (i.e., for firms with more than 10,000 employees). In other words, considering all firms which have above 10,000 employees in one big class may potentially flatten the slope of the fitted line, and therefore, may reduce the power-law parameter. Second, as argued by Gabaix (2009), for regions with high volatility in firm size, the power-law parameter can be smaller than 1.

but it also has a *large* decay rate, this fat-tailed distribution might not be "fat" enough. In this case, it might be difficult to empirically identify this state as granular.

Our conjecture is motivated by the self-similarity property of fat-tailed distributions. This property suggests that adding two fat-tailed distributions with different tail decay rates produces a fat-tailed distribution that has the *smallest* decay rate. Therefore, the tail decay rate of the U.S. firm size distribution should be driven by the smallest decay rate among the U.S. *state* distributions. That is, at the national level we always have a size distribution with a small decay rate. In contrast, at the state level, we might have a fat-tailed distribution, but a large decay rate that can make it empirically difficult to identify a state as granular.[12]

To investigate the above hypothesis, we study the pre- and post-tail behavior for states with power-law distributions. Similar to the previous analysis, we use firms' employees to measure their size. We set the beginning of the distribution's tail where the number of employees exceeds 500. We use this criterion for two main reasons: (1) SBA classifies firms with more than 500 employees as large companies, and (2) the number of firms significantly drops in each state, as firm employees exceed 500.

Next, we fit power-law distributions to states' *pre-tail* data and identify the fat-tailed distributed states that also have a power-law distribution before their tails. They are California, Texas, Wisconsin, New York, New Jersey, and Florida. We consider these states as local economies with a fat-tailed distribution and a small tail decay rate and depict their geographic distribution in Figure B2. Consistent with our hypothesis, we find that the majority of the fat-tailed states, which also have a small tail decay-rate, are among the granular economies. This evidence suggests that the tail decay rate (in addition to fat-tailed feature) is an important factor in empirically identifying the granularity effect.[13]

[12]In Appendix B, we provide a more detailed discussion of the importance of a small decay rate on the granularity of local economies.

[13]Although firm size distribution in New York is fat-tailed with a small tail decay rate, this state is not among the granular states of Table 2. We conjecture that excluding the top-100 U.S. firms from the analysis of Regression (5) may contribute to the smaller estimated R^2 for New York. In particular, a large number of nationally large firms are headquartered in New York, which may affect the size distribution and granularity of the state. Confirming this conjecture, we find that re-estimating Regression (5) with the sample of top-100 firms raises the estimated R^2 for New York to over 10%.

To further examine the above finding, in Table B2 we show the correlation between granularity of states with fat-tailed firm size distributions (i.e., the estimated R^2 from Regression (5)) and their tail decay rate. Column (1) of Table B2 shows the 11 U.S. states with a fat-tailed distribution of firm sizes. In Column (2) we show the pre-tail exponent of size distribution. In Column (3), we report the estimated R^2 from Regression (5). If our conjecture about the role of tail decay rate on the granularity of local economies is valid, the highest level of R^2 should belong to states with the lowest value of tail decay rate (i.e., the highest value of pre-tail exponent). Our results in Table B2 confirms this hypothesis: there is a negative correlation of 73% between state-level granularity and tail decay rate of size distribution. This correlation is statistically significant at the 5% level confidence level. Overall, these results suggest that the tail decay rate of size distribution is an important factor that affects the granularity of local economies.

3.4 Firm Network and Empirical Tests of Granularity

As explained in Acemoglu et al. (2012), firms' networks may also lend to slow diffusion of idiosyncratic shocks, even in the absence of fat-tailed firm size distribution. Indeed, the evidence in Table 2 suggests the granularity effect of some states in which firm size distribution is not heavily right-skewed (i.e., Vermont, Mississippi, Arizona, Indiana, Alabama, Oklahoma, Nevada, and New Mexico). We conjecture that the network structure between firms in these states leads to slow diffusion of shocks to dominant firms, which in turn, causes the documented granular effect. An empirical test of this conjecture requires detailed information about firms' connections. Such information, however, is not easily obtained through public databases. Despite this limitation, we attempt to test the hypothesis, using return co-movements of firms as a proxy for their connectivity.

Specifically, each month, we run the following rolling regression, with a 36-month rolling window (Bernile et al., 2015):

$$\begin{aligned} Excess\ Return_{i,j,t} &= \alpha + \beta_1\ Market\ Excess\ Return_t + \\ \beta_2\ Dominant\ Firms\ Excess\ Return_{j,t} &+ \beta_3\ SBM_t + \beta_4\ HML_t + \varepsilon_{i,j,t}, \end{aligned} \tag{10}$$

where, $Excess\ Return_{j,t}$ shows the monthly excess return of non-dominant firm i, headquartered in state j at time t. $Market\ Excess\ Return_t$ is the monthly excess return for the value-weighted market portfolio. $Dominant\ Firms\ Excess\ Return_t$ shows the monthly excess return for the portfolio of locally dominant firms that are headquartered in the same state as the non-dominant firm. To additionally control for other known risk factors, we add Fama and French's (1993) size (*SMB*) and value (*HML*) factors to the regression.[14] Our main coefficient of interest is β_2, which shows the co-movement of the non-dominant firm's returns with those of dominant firms in the same state. A state with stronger co-movement of returns between dominant and non-dominant firms is expected to have stronger firm connections, and hence, a granular economy.

Testing the above idea, we first measure the monthly average of β_2 in each state and then calculate the correlation between these average betas with the estimated R^2 from Regression (5). If our conjecture is valid, the correlation between β_2 and R^2 should be positive. This is indeed what we find. As shown in Columns (2) and (5) of Panel A in Table B3, among states that do not have a fat-tailed firm size distribution, the correlation between these two variables is 16.14%. This correlation is equal to 14.36% when we restrict the sample to granular states that have a non-fat-tailed firm size distribution (Panel B of Table B3).

Given that the discount rate and cash flows affect firms' return, we next investigate the role of fundamental values on the above findings. In doing so, we estimate the exposure

[14] Our results remain consistent if we change the estimation window to 24-month, or if we further include Carhart's (1997) momentum factor in our model.

of non-dominant firms' fundamentals to those of locally dominant firms in the same state, running the following rolling regression with 36-month window:

$$\begin{aligned} Operating\ Income\ Growth_{i,j,t} = \alpha + \beta_1\ Market\ Operating\ Income\ Growth_t + \\ \beta_2\ Dominant\ Firms\ Operating\ Income_{j,t} + \varepsilon_{i,j,t}, \end{aligned} \tag{11}$$

where $Operating\ Income\ Growth_{i,j,t}$ shows the growth in operating income after depreciation for firm i, headquartered in state j at time t. $Market\ Operating\ Income\ Growth_t$ shows the average growth in operating income of all firms, excluding locally dominant firms in state j and firm i, and $Dominant\ Firms\ Operating\ Income\ Growth_{j,t}$ shows the average growth in operating income of locally dominant firms in state j. As before, we are interested in the correlation between the average value of β_2 and the estimated R^2 from Regression (5).

The results in Columns (3) and (5) of Panel A in Table B3 indicate a statistically significant correlation of 43.58% for states with non-fat firm size distribution. This number further raises to 72.78% when we restrict the sample to granular states (see Panel B). The same pattern holds when we use an alternative measure of firms' fundamentals (i.e., Cash flows from Operating Activities Growth in Columns (4) of Panel A).

Lastly, in untabulated results, we use Hoberg and Phillips's (2016) text-based network industry classification (TNIC) data to examine whether firm-level connections affect the granularity of local economies. Using firms' 10-K filings, the TNIC data provide a score that captures similarities between firms' product markets. We use this information to measure the annual score value for pairs of locally dominant firms and other non-dominant firms that are headquartered in the same state. We then examine whether a higher level of overlaps between the product markets of firm pairs (i.e., higher average score) is correlated with a higher level of granularity (i.e., a higher estimated R^2 from Regression (5). We find that the correlation between these variables is equal to 18% (statistically insignificant at the conventional levels).

These results confirm that in states in which operations of non-dominant firms have a higher exposure to those of locally dominant firms, the diffusion of firm-level shocks is slower, and therefore, firm-level shocks may cause aggregate effects on the local economy. Together, the analysis of this section provides empirical evidence for theories that explain the granularity of local economies. In Appendix C, we further identify the groups of firms that affect the economy of non-granular states.

4 Aggregate Impact of the Granular States

In this section, we demonstrate the economic importance of the granular states and examine whether shocks to locally dominant firms in these states have any aggregate effects.

4.1 Locally Dominant Firms and Regional GDP Growth

We begin by investigating whether shocks to locally dominant firms in a granular state impact the out-of-state economies. Specifically, we study the role of locally dominant firms on the economies of states that (1) share the same division, or (2) share a border with the granular states.

For each granular state, we first calculate idiosyncratic shocks of locally dominant firms using Equations (2) and (3). Next, we calculate the real GDP per capita of division (region) z to which the granular state belongs to by adding the real GDP of all states located in the division (region). Using states' population data we then calculate the real aggregate GDP per capita for the division (region). Next, we measure the granular residual of locally dominant firms in the granular state (i.e., $\Gamma_{j,t}$), similar to Equation (4), but we replace the state-level GDP by the division- (region-) level GDP. Next, to examine the economic power of $\Gamma_{j,t}$ on the division's (region's) economy, we run a time-series regression similar to Regression (5) where the dependent variable is $GDP\ Growth_{z,t}$ and the main independent variables are $\Gamma_{j,t}$ and $\Gamma_{j,t-1}$.

Table 5 shows the granular states that have predictive power in explaining their divisions' (or regions') business cycles. Specifically, in Panel A of Table 5 we show the granular states that have an aggregate impact on the economic growth of their divisions. Overall, we find that productivity shocks to the locally dominant firms in 11 (out of 13) granular states can explain an important portion of the economic growth of their divisions. For example, we find that a one-standard-deviation increase to the granular residual of locally dominant firms in California is associated with a 42-pps increase in the standard deviation of Pacific division's GDP growth ($\Gamma_{j,t} = 0.426$ (t-statistic $= 3.73$); $\Gamma_{j,t-1} = 0.351$ (t-statistic $= 3.57$)). Moreover, the results indicate that productivity shocks to locally dominant firms in California explain 31% of the economic fluctuations in the Pacific division.

Similarly, the granular residual of firms in Florida significantly affect the GDP growth of South Atlantic ($\Gamma_{j,t} = 0.417$ (t-statistic $= 3.02$); $\Gamma_{j,t-1} = 0.178$ (t-statistic $= 2.23$)). Further, shocks to locally dominant firms in Florida explain over 20% of South Atlantic's business cycles. Our results indicate a similar pattern for other granular states. Specifically, the explanatory power of the granular residual measure ranges from 18.1% for locally dominant firms in Indiana to 8.2% for locally dominant firms in Wisconsin.

In Panel B of Table 5 we show those granular states that have a significant economic effect on their regions. We find that shocks to locally dominant firms in 11 granular states have explanatory power for their regional economic growth. Similar to the results in Panel A, the estimation results here also indicate that the granular residual of locally dominant firms significantly affects the GDP growth of their regions. In case of California, for example, the point estimates for $\Gamma_{j,t}$ and $\Gamma_{j,t-1}$ are equal to 0.010 (t-statistic $= 3.83$) and 0.009 (t-statistic $= 3.52$), respectively. Moreover, productivity shocks to locally dominant firms headquartered in California can explain 30.5% of the economic growth in states that share a border with California (i.e., Oregon, Arizona, and Nevada). This explanatory power remains economically meaningful in other granular states, ranging from 25.3% for locally dominant firms in Florida and Nevada to 9.4% for locally dominant firms in Texas. Collectively, these results indicate that shocks to locally dominant firms do not average out at the aggregate divisional (or regional) level.

4.2 Locally Dominant Firms and U.S. GDP Growth

The natural next step is to examine the aggregate impact of locally dominant firms in the granular states on the national economy. Moreover, it is important to compare the predictive power of these firms with the economic power of nationally large firms for U.S. GDP growth. To identify the economic effects of the locally dominant firms on the U.S. business cycle, we run a regression similar to Regression (5) with U.S. GDP growth as our dependent variable.

We present the regression results in Table 6. To set the stage, in Column (1) of Table 6 we present a regression results related to the predictive power of the productivity shocks of the top-100 U.S. firms on national GDP growth. Similar to the finding in Gabaix (2011), our results suggest that shocks to top-100 U.S. firms are able to explain 24.2% of U.S. GDP growth ($\Gamma_{top100,t}$ = 0.502 (t-statistic = 3.01); $\Gamma_{top100,t-1}$ = 0.261 (t-statistic = 2.34)).

Next, in Column (2) of Table 6 we present the economic effects of locally dominant firms in the granular states on U.S. GDP growth. To calculate the granular residual of locally dominant firms (i.e., $\Gamma_{dom,t}$), we first use Equations (2) and (3) to calculate firms' idiosyncratic shocks. Next, we use an equation similar to Equation (4), but we replace the state-level GDP with U.S. GDP. Next, we repeat our time-series regression, using $\Gamma_{dom,t}$ and $\Gamma_{dom,t-1}$ as main independent variable. We find that the predictive power of locally dominant firms is comparable to that of top-100 U.S. firms. In particular, shocks to the locally dominant firms are able to explain 47.8% of the U.S. economic fluctuations ($\Gamma_{dom,t}$ = 0.663 (t-statistic = 4.75); $\Gamma_{dom,t-1}$ = 0.295 (t-statistic = 2.58)).

Although locally dominant firms are considerably smaller than the largest firms in the U.S. (see Table A2), their impact on the national business cycle is economically large. Our estimates from Column (2) indicate that a one-standard-deviation increase in the granular residual of locally dominant firms is associated with a 48-pps increase in the standard deviation of U.S. GDP growth. Similarly, the estimate in Column (1) suggests that a one-standard-deviation increase in the granular residual of the top-100 U.S. firms is associated with a 38-pps increase in the standard deviation of U.S. GDP growth.

In Column (3) of Table 6, we study the cumulative explanatory power of locally dominant and top-100 firms. That is, we estimate a regression that include the granular residuals of the locally dominant and top-100 U.S. firms. Together, the granular residual of these firms are able to explain about 52.4% of the U.S. business cycle. We also find that when we consider the joint effects of locally dominant and top-100 U.S. firms, the influence of the locally dominant firms is not significantly affected. Specifically, the coefficient of $\Gamma_{dom,t}$ (i.e., the granular residual of locally dominant firms in the granular states) only declines from 0.663 (t-statistic = 4.75) to 0.570 (t-statistic = 4.05).[15]

Overall, we find that shocks to locally dominant firms affect the economic growth of their headquarter states and also have an aggregate impact on the out-of-state economies. Moreover, the aggregate effect of these firms on the national GDP growth is statistically and economically comparable to the effect of nationally large firms.

4.3 Mechanism: From the U.S. States to the U.S. Economy

The results in Table 6 suggest that shocks to locally large firms aggregate and their effects propagate to the national economy. We conjecture that this propagation mechanism starts with the locally dominant firms affecting the business cycle of their state economy. Then, changes in the state business cycle spillover to the regional economy and ultimately to the national economy.

If our conjecture about how local firm shocks affect the national economy is correct, then firm shocks that have a strong impact on their local economy should have the strongest impact on the national economy. In other words, the granularity of U.S. states should serve as a barometer of which firm-shocks are the most important for U.S. GDP growth. To test this idea, we re-examine the aggregate effects of granular states by accounting for the *level* of granularity at the state and the region/division level in each state.

[15] In unreported results, we repeat the analysis of Table 6, but only consider those granular states for which the estimated Γ_t in Table 2 is statistically significant at the 5% confidence level (i.e., California, Florida, Vermont, Nevada, Mississippi, and Nevada). This restriction leads to a consistent outcome as before. In particular, we find the following point estimates: $\Gamma_{dom,t}$= 0.591 (t-statistic = 4.41), and $\Gamma_{dom,t-1}$ = 0.234 (t-statistic = 1.97) with R^2= 47.4% (Adj. R^2= 44.3%).

To study the role of granularity at the state-level, we use the estimated R^2 from Table 2 to create aggregation weights. In particular, we first use Equation (4) to calculate the granular residual for each granular state. Next, we use the R^2-based weights to create our weighted granular residual measure. In this way, shocks to locally dominant firms headquartered in California, for example, get a larger weight because the estimated R^2 for California is greater compared to other granular states. We expect that a higher level of granularity (at the state-level) should create a higher level of aggregate impact on the national GDP growth.

We estimate the baseline regression (from Section 4.2) with the new weighted average of granular residual and present the estimation results in Table 7. Panel A shows the estimation results, using state-level granularity as our weighting matrix. The estimates in Column (1) show that when we account for the level of the state's granularity, the predictive power of locally dominant firms increases from 47.8% (in Table 6) to 53.9% ($\Gamma_{dom,t} = 0.564$ (t-statistic $= 4.50$); $\Gamma_{s,t-1} = 0.393$ (t-statistic $= 3.23$)). Further, the results in Column (2) suggest that when we consider the cumulative effects of the top-100 U.S. firms and locally dominant firms, the R^2 also increases from 52.3% (in Table 6) to 62.2%. These findings confirm our conjecture that states with higher levels of granularity have higher levels of influence on the U.S. fluctuations.

In Panels B and C of Table 7, we examine the effects of granularity at the division and region levels. For these tests, we create two new sets of aggregation weights, using the estimated R^2 from Columns (4) and (8) of Table 5. We use the new weights and compute weighted averages of the granular residual of locally dominant firms.

Similar to the previous estimates, the results in Columns (3) to (6) of Table 7 show that accounting for the out-of-state impact of locally dominant firms increases the estimated R^2. Specifically, when we use the division and region granularity for the new Γ_t's, the R^2 become 52.9% and 55.6%, respectively (see Columns (3) and (5)). Moreover, the cumulative explanatory power of locally dominant firms and top-100 U.S. firms rises to 60.9% when using the division granularity, and to 62.2% when using the region granularity weights (see Columns (4) and (6), respectively).

Although the above method allows us to account for the granularity of state in our aggregate analysis, it may raise the concern of overestimating the influence of large states, like California. While California, as the most granular state in our analysis, receives the highest weight in the analysis of Table 7, not all large states are treated similarly. For instance, a state like Vermont receives a higher weight compared with a relatively larger state like Texas. However, to ensure that our weighting method does not overestimate the impact of few states with a larger number of locally dominant firms, in Table A3, we repeat the above analysis but drop those states that have the highest number of dominant firms (i.e., CA, TX, FL, and NJ) and find a similar outcome. This evidence suggests that although large states affect the aggregate influence of locally dominant firms, they are not the sole driver of our results. Collectively, the evidence in Table 7 suggests that shocks to local firms propagate across the U.S. economy and its effects ripple geographically from state to state. This is the case because locally dominant firms that affect their local economies the most, seem to have the strongest effect on the U.S. economy.

5 Robustness Checks and Additional Evidence

In this section, we provide results from various robustness tests for our baseline analysis. We report the results for the analysis of this section in Appendix A.

5.1 Relevance of Locally Dominant Firms for Their HQ States

One concern regarding the economic effects of locally dominant firms is that these firms may have out-of-state operations. Therefore, a locally dominant firm's net sales may not necessarily reflect the company's real contribution to its HQ state's GDP. As argued by Gabaix (2011), there is not an easy way to address this issue using the information provided in the Compustat database. However, we attempt to address this concern using the information on the geographical dispersion of the economic interest of firms across the U.S. states.

Specifically, we follow a methodology similar to Garcia and Norli (2012) and Bernile et al. (2020). These authors note that all U.S.-based companies are required to annually file Form 10-K with the U.S. Securities and Exchange Commission (SEC). Each 10-K has prescribed reporting and disclosure items that contain an overview of a firm's business operations, financial conditions, and audited financial statements. Focusing on items 1, 2, 6, and 7 of each 10-K filing; that is, sections of 10-K that are most relevant for the firm's operations and performance, Bernile et al. (2020) identify the exposure of firms to a particular state, by conducting a textual analysis of firms' 10-K filings. Specifically, for each annual filling from 1994 to 2012, Bernile et al. (2020) count the number of times a state is cited in the above four sections of the 10-K form of each firm and argue that the more a state is cited in a firm's filling, the more that state is economically relevant for the firm.

Using the above information, we determine whether a firm's HQ state is among the *top-3* most cited states for the firm. This information allows us to identify locally dominant firms that are also "economically present" in their HQ states. Restricting our sample to these companies, we repeat the analysis of Table 2, and present the new results in Panel A of Table A4. The results indicate that even after excluding locally dominant firms that are *not* economically present in granular states, the remaining locally dominant firms have significant explanatory power over granular states' fluctuations. Further, for some of the granular states, the predictive power of granular states increases when we restrict the sample to locally dominant firms that are economically present in their HQ states. For example, the predictive power of locally dominant firms in Oklahoma increases from 12.2% (in Table 2) to over 68%. Similarly, the aggregate influence of locally dominant firms in Indiana increase from 12.8% (in Table 2) to 37%.

As an alternative method, we use the geographical segment of the Compustat database to identify and exclude those locally dominant firms with international sales. This method allows us to restrict the sample to dominant firms that their businesses are locally focused. Using the new set of dominant firms, we re-run Regression (5) and show the results in Panel B of Table A4.[16] Again we find that, even after excluding dominant firms with international

[16] The sample period used in Panels A and B of Table A4 are not identical. For this reason, the numbers of locally dominant firms in these two panels are different.

operations, the remaining firms continue to explain a considerable portion of their states' business cycles. Together, these analyses indicate that although dominant firms with out-of-state operations affect the local business cycles, the documented impact of locally dominant firms is not merely driven by these firms.

5.2 Alternative Measures of Idiosyncratic Productivity Shocks

In our baseline analysis in Section 3, we used a method similar to Gabaix (2011) to calculate firms' idiosyncratic shocks. This measure, however, assumes a homogeneous exposure of all firms to market-wide shocks. Moreover, one could be concerned that industry-level shocks may also affect the productivity growth of locally dominant firms and other firms in the same HQ state. To address these issues, we employ three additional methods of identifying firm-level productivity shocks.

First, to account for heterogeneous exposure of firms to common shocks, we build a measure of productivity shocks, using the residual ($\varepsilon_{i,j,s,t}$) of the following pooled-panel regression:

$$\begin{aligned} \textit{Productivity Growth}_{i,s,j,t} = \alpha_j + \beta_i^s\ \textit{Productivity Growth}_{s,t} + \\ \beta_i^j\ \textit{Productivity Growth}_{j,t} + \varepsilon_{i,s,j,t}. \end{aligned} \tag{12}$$

Above, $\textit{Productivity Growth}_{i,s,j,t}$ is the productivity growth of firm i in industry s, headquartered in state j at time t (Equation (2)). $\textit{Productivity Growth}_{s,t}$ shows the average productivity growth of firms in sector s at time t.[17] $\textit{Productivity Growth}_{j,t}$ shows the average productivity growth of firms headquartered in state j at time t. The estimated residual ($\varepsilon_{i,s,j,t}$) captures firm-level idiosyncratic productivity shocks, over and above common industry- and geography-wide shocks. Using the estimated residual as our main measure of firms' idiosyncratic productivity shocks, we calculate the granular residual in each state following Equation (4) and repeat Regression (5). Column (1) in Panel A of Table A5 shows that among the previously identified granular states, idiosyncratic shocks to the locally

[17] We use the Fama-French 48 industry portfolios to identify firm industries.

dominant firms in California, Vermont, Mississippi, Indiana, Oklahoma, New Jersey, and Texas significantly affect the state-level economic fluctuations.

One could also argue that the scaling method of Equation (4) may affect the above results. This method is motivated by Hulten's (1978) theorem, in which a firm that accounts for a bigger proportion of the (local) GDP receives a higher weight in the analysis. Although other studies (e.g., Gabaix, 2011; Foerster et al., 2011) also use this scaling method, to ensure that our results are not sensitive to this weighting assumption, we repeat our analysis in Column (1) but assign equal weight to locally dominant firms' shocks. The results in Column (2) of Panel A show similar effects as before. Specifically, we continue to find that productivity shocks to locally dominant firms in California, Vermont, Mississippi, Indiana, Oklahoma, New Jersey, and Texas explain a significant portion of the local economic growth.

For our second alternative method, we examine the influence of common-industry shocks, using Standard Industry Classification (SIC). We use this classification to further show the robustness of our results to a broader classification of firms' sectors. In particular, we re-calculate firms' productivity shocks as the difference between their productivity growth and the average productivity growth of firms in the same sector, using 3- (and 2-) digits SIC codes to identify firms' industries. Using these shocks, we re-estimate Regression (5) and report the results in Panel B of Table A5. The overall evidence suggests that shocks to locally dominant firms still explain a significant portion of the local business cycles, however, compared with the baseline results, the magnitude of the estimated R^2s are now smaller.

In the above analyses, we have assumed that industry- and state-level shocks are the common shocks that affect firms' productivity growth. However, it is possible that other (unknown) common shocks may influence our identification. Therefore, in our third alternative method, we use principle of component analysis (PCA) to identify common factors that explain the variation of state-level business cycles and productivity growth of firms (Bai and Ng, 2002). Specifically, we run the following regressions:

$$State\ GDP\ Growth_{j,t} = \beta \times F_t + \varepsilon_{j,t}, \tag{13}$$

and,

$$Productivity\ Growth_{i,j,t} = \beta \times F_t + \varepsilon_{i,j,t}, \tag{14}$$

where, $State\ GDP\ Growth_{j,t}$ is the GDP growth of state j at time t and $Productivity\ Growth_{i,j,t}$ shows the productivity growth of firm i, headquartered in states s at time t. Lastly, F is a vector of unobserved common factors that jointly explain the variations in state GDP growth and those of firms' productivity growth.

In the above equations, we don't impose restrictions on the number of common factors, allowing the data to identify the total number of factors that explain the variations of the dependent variables. Our analysis identifies two factors, with the Eigen value (proportion of explanation) of 1.0512 (0.5256) for factor 1 and 1.0512 (0.4744) for factor 2, respectively. Using the estimated factors, we run the following regression and use the estimated residual ($\varepsilon_{i,t}$) as our new proxy for firm-level productivity shocks:

$$Productivity\ Growth_{i,t} = \alpha_i + \beta_i^1\ Factor_{1,t} + \beta_i^2\ Factor_{2,t} + \varepsilon_{i,t}. \tag{15}$$

Next, we re-estimate our baseline analysis and report the results in Panel C of Table A5. As shown, out of the 13 identified granular states, shocks to locally dominant firms in all states (expect for Arizona and New Jersey) continue to explain a significant portion of the local economic fluctuations.

5.3 Expanding the Sample Size of Locally Dominant Firms

So far, we have considered firms that are among the top-quartile largest firms in their HQ states as locally dominant. We choose this cutoff to ensure that, while we consider the few largest local firms, our sample of locally dominant firms in each state is large enough to gain statistical power. This method, however, may introduce noise in our time-series estimation because the sample size in some states may remain small. In fact, the results in Table 2 indicate that, in some states, the estimated Γ_ts are not statistically significant at the 5% level confidence (e.g., Arizona and Indiana). Therefore, in this section, we expand the sample of locally dominant firms to firms that, after excluding the top-100 U.S. firms, are among the top-tercile largest firms in their HQ states. Next, we re-estimate our baseline regression (Equation (5)) and report the results in Table A6. As shown, expanding the sample size increases the statistical power of Γ_ts (for instance the t-statistic in 2 increase from 1.22 to 2.94 for Arizona, and from 1.84 to 2.49 for Indiana).

We also investigate if the change in the sample of locally dominant firms affects the aggregate influence of these firms on the U.S. GDP growth. In doing so, we use the above sample and re-estimate the analysis of Table 6. The results in Panel B of Table A6 indicate that the aggregate effect of locally dominant firms remains consistent ($R^2 = 53.1\%$) and as before, this impact is comparable to the effects of nationally large firms.

5.4 Effects of Large Shocks

In this section, we examine the influence of large productivity shocks on our results. In doing so, we follow Gabaix (2009) and account for the effects of large shocks by winsorizing demeaned productivity growth. Specifically, we use three different cut-offs of 5%, 10%, and 20% to winsorize Equation (2) and re-calculate granular residuals of each state. Next, we repeat Regression (5) and report the results in Table A7. The results indicate that, even after winsorizing the productivity growth rate, shocks to locally dominant firms continue to affect the local business cycle in the identified granular states.

To gain an overview of the previous robustness tests, in Table A8, we report the estimated R^2 of each method for each granular state, along with the average R^2 obtained from these tests. We also rank granular states based on the average R^2s of the robustness analysis and compare this rank with the baseline analysis in Table 2. The results show that, although the estimated R^2 varies in each method, the average R^2 of the granular state remains considerable.

5.5 Impact of Locally Dominant Firms beyond Other Shocks

In Section 4.2, we showed that the aggregate influence of shocks to locally dominant firms is comparable to those of the top-100 U.S. firms. To additionally show that this impact remains robust beyond the impact of other macro shocks, we repeat the same analysis of Table 6 but further control for oil and monetary shocks. Specifically, we follow the same method as in Gabaix (2011) and use Hamilton (2003) and Romer and Romer (2004) shocks to proxy for oil and monetary shocks, respectively.[18] We also control for other financial factors, such as the interest rate and term spread, that may affect the U.S. GDP growth.

Table A9 shows the results. As before, productivity shocks to locally dominant firms continue to explain a large portion of the aggregate economic fluctuations ($R^2 = 46.3\%$ in Column (3)). This result holds in Columns (4) to (8) when we control for the impact of oil and monetary shocks and other financial variables. To further show the influence of our measures on the national business cycles, we report the joint F-test for $\Gamma_{dom,t}$ and $\Gamma_{dom,t-1}$ (i.e., the granular residual of dominant firms). As shown, the F-tests for these two variables are statistically significant at the 10% confidence level, confirming their role in explaining the aggregate economic growth.

5.6 Only Top-100 Locally Dominant Firms

In Section 4.1 we showed that the economic impact of locally dominant firms on the U.S. GDP growth is comparable to the effect of nationally large companies (i.e., top-100 U.S. firms). However, this effect might be driven by the fact that the sample of locally dominant firms is larger compared to the top-100 U.S. firms. We, therefore, restrict our sample of locally dominant firms to the top-100 largest locally dominant firms.[19] In this way, the granular residual of the locally dominant firms is more consistent with the work of Gabaix (2011).

[18] We collect these data, using the supplementary material provided by Gabaix (2011).

[19] To create our aggregate granular measure, we follow the same method described in Section 4.2.

Table A10 shows the results with the top-100 locally dominant firms. In Column (1) we show the estimation results for the sample of top-100 locally dominant firms. As shown, the new local granular measure produces slightly lower R^2 estimate (42.4% vs. 47.8%). Nevertheless, the point estimates for $\Gamma_{dom,t}$ and $\Gamma_{dom,t-1}$ remain economically and statistically significant ($\Gamma_{dom,t} = 0.633$ (t-statistic = 4.23); $\Gamma_{dom,t-1} = 0.282$ (t-statistic = 2.26)). Moreover, the estimation results in Column (2) indicate that the predictive power of locally dominant firms in the granular states is still comparable to that of the top-100 firms. Our results also show that the cumulative explanatory power of the top-100 largest locally dominant firms and the top-100 largest companies in the U.S. is 49.3%, which is similar to our baseline estimate in Table 6.

Additionally, we examine whether our sample of locally dominant firms, which does not include the top-100 U.S. companies, simply includes the second 100 largest U.S. firms. In unreported results, we find that more than 90% of locally dominant firms in granular states are not even among the U.S. top-200 firms. Therefore, we argue that the aggregate effect of locally dominant firms in granular states cannot be uncovered by simply relaxing the definition of the top national firms.

5.7 Extending the Sample Period

Additionally, we perform our baseline empirical analysis using a longer period. As explained in Section 2, due to data limitations, our sample starts in 1977. However, to ensure that our results are robust to a longer period, we use nominal GDP per capita to compute the GDP growth from 1963 to 2017.

Although the nominal GDP per capita is not a perfect proxy for economic growth, it allows us to extend our sample backward. Using the extended sample, we reestimate our baseline regression. As shown in Column (3) of Table A10, our overall inferences are robust to using the extended sample. Similar to the findings in Table 6, productivity shocks to locally dominant firms and top-100 U.S. firms explain almost 45% of aggregate fluctuations.

Further, the economic effects of locally dominant firms are still comparable to the effects of nationally large firms.

5.8 Alternative Measure of Productivity Growth

Finally, we examine the robustness of our results, using an alternative measure of firm productivity growth. In doing so, we obtain firm-level total factor productivity (TFP) data from İmrohoroğlu and Tüzel (2014). Using information on firms' plant, property, and equipment ($k_{i,t}$), number of employees ($l_{i,t}$), and value added ($y_{i,t}$), İmrohoroğlu and Tüzel (2014) estimate firms' TFP ($w_{i,t}$), using a semi-parametric procedure for the following equation (see Appendix A of İmrohoroğlu and Tüzel (2014) for more information):

$$y_{j,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + w_{i,t} + \eta_{i,t}. \tag{16}$$

Based on the estimated TFP from the above regression, we measure firm-specific productivity shocks similar to Equation (3), and re-estimate our baseline analysis. Table A11 shows the estimation results. As shown, in 9 granular states, that is, California, Vermont, Mississippi, Alabama, Arizona, Indiana, Nevada, New Mexico, and Texas, firm-specific shocks to locally dominant firms remain a significant determinant of local business cycles.

6 Summary and Conclusions

Understanding the origins of macroeconomic fluctuations is important. While recent papers focus on the origins of the U.S. business cycle, research on the determinants of local economic growth and state-level business cycles has received limited attention. In this paper, we study the economic effects of locally dominant firms, i.e., firms that are big in their local areas but are not among the largest U.S. firms.

We use the Gabaix's (2011) method to identify locally dominant firms that are not among the largest 100 U.S. firms but have a strong impact on their local macroeconomic environment. Specifically, we consider firms in the top quartile of revenues in each state as locally dominant firms. We find that in 13 (granular) states, productivity shocks to locally dominant firms explain a significant portion of the state-level GDP growth. Further, we find that idiosyncratic shocks to locally dominant firms explain a significant portion of the local business cycle as well as the aggregate U.S. macroeconomic fluctuations. Specifically, productivity shocks to locally dominant firms explain almost 50% of U.S. GDP growth.

Our findings complement previous studies that examine the role of firm-level shocks on the aggregate economic fluctuations. Specifically, we provide an additional firm-level explanation (i.e., shocks to locally dominant firms) for the U.S. business cycle. This finding is important because the influence of shocks to locally dominant firms is comparable to the effect of the largest U.S. firms. We also show that the tail decay rate of firm size distribution is an important factor in empirically identifying granular economies. This finding extends the prior literature (e.g., Gabaix, 2011; Acemoglu et al., 2012) that examines the theoretical reasons for the granularity of an economy.

In future work, it would be useful to examine whether our findings have implications for financial markets. For instance, the propagation of firm-level shocks may generate co-movement among the returns of affected firms. Further, the link between idiosyncratic shocks and the local business cycle may provide new insight into the origins of local financial risk, which in turn could affect corporate policies.

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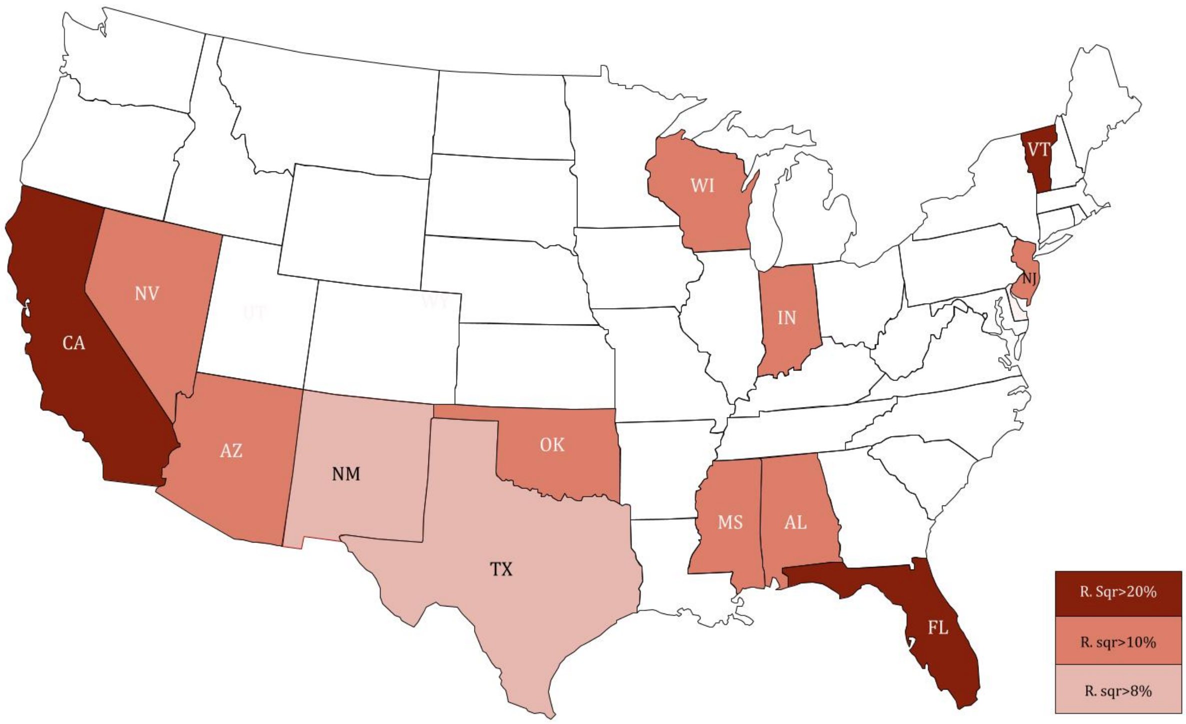

Figure 1: **Geographic Distribution of Granular States**
This figure shows the geographic distribution of granular states. Specifically, in the identified states, productivity shocks to locally dominant firms explain more than 8% of the state's GDP growth. States in which locally dominant firms have a larger economic impact are shown in a darker shade. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per capita is from the BEA. The sample period is from 1977 to 2017.

Table 1: **Summary Statistics**

This table presents summary statistics of the main variables used in the empirical analysis. *Sales* is the net sales of firms, *Employees* is the total number of employees, *Productivity Growth* is the annual log change in firms total sales per number of employees. *Granular residual* is the weighted average of idiosyncratic productivity shocks for the group of locally dominant firms (Equation (4)). State *GDP Growth* is the log change of state's real GDP per capita. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017.

State	Variable	Mean	P25	P50	P75	Std.	State	Mean	P25	P50	P75	Std.	State	Mean	P25	P50	P75	Std.
AK	Sale ($ Million)	319	96	325	391	247	FL	897	18	75	422	2871	KY	1405	84	322	1228	2484
	Employees (in 1000)	0.968	0.529	0.973	1.255	0.556		6.002	0.146	0.571	2.639	19.861		16.56	0.65	2.2	12.7	54.932
	Annual Productivity Growth	0.02	-0.021	0.031	0.08	0.114		0.04	-0.053	0.043	0.142	0.18		0.039	-0.032	0.045	0.116	0.151
	Granular Residual	0.000	0.000	0.000	0.000	0.000		-0.001	-0.003	0.000	0.003	0.007		0.000	-0.002	0.000	0.001	0.006
	Annual Number of Firms	1.778	1	2	2	0.604		189.64	152	194	231	44.087		21.032	19	22	24	3.711
	Annual GDP Growth	0.008	-0.021	0.007	0.035	0.047		0.014	0.009	0.016	0.028	0.024		0.013	-0.001	0.015	0.027	0.027
AL	Sale ($ Million)	620	91	228	601	1062	GA	2168	70	278	1134	7036	LA	1100	48	232	748	2776
	Employees (in 1000)	4.585	0.698	1.646	5.02	8.497		11.805	0.523	1.988	7.75	39.189		5.028	0.283	1.5	5.2	10.394
	Annual Productivity Growth	0.041	-0.034	0.037	0.119	0.151		0.046	-0.032	0.047	0.127	0.158		0.039	-0.042	0.042	0.131	0.163
	Granular Residual	0.002	-0.001	0.000	0.001	0.008		0.000	-0.003	-0.002	0.003	0.007		0.001	-0.002	0.000	0.004	0.007
	Annual Number of Firms	20.727	18	21	24	5.547		107.814	83	104	133	28.988		21.407	19	21	25	4.074
	Annual GDP Growth	0.018	0.005	0.023	0.031	0.02		0.017	0	0.02	0.034	0.026		0.01	-0.002	0.013	0.031	0.031
AR	Sale ($ Million)	13000	111	492	2342	61000	HI	392	11	78	547	569	MA	651	23	91	339	2349
	Employees (in 1000)	72.843	0.915	3.69	14.667	316.529		1.611	0.052	0.632	2.715	2.223		4.076	0.175	0.639	2.5	12.906
	Annual Productivity Growth	0.044	-0.022	0.043	0.11	0.144		0.044	-0.016	0.053	0.133	0.161		0.045	-0.041	0.051	0.138	0.169
	Granular Residual	0.000	-0.003	0.000	0.002	0.012		0.000	-0.001	0.000	0.000	0.004		0.000	-0.002	0.000	0.002	0.005
	Annual Number of Firms	17.955	14	17	21	3.782		7.73	7	7	9	1.929		195.862	163	189	230	41.835
	Annual GDP Growth	0.018	0.005	0.019	0.033	0.023		0.009	-0.003	0.012	0.023	0.025		0.025	0.008	0.024	0.044	0.026
AZ	Sale ($ Million)	1093	39	208	905	2707	IA	610	32	224	735	1044	MD	1052	19	90	482	4130
	Employees (in 1000)	4.843	0.287	1.5	5.486	8.031		3.222	0.295	1.856	3.85	4.688		7.201	0.172	0.69	3.189	22.41
	Annual Productivity Growth	0.046	-0.043	0.053	0.148	0.174		0.042	-0.03	0.045	0.119	0.144		0.046	-0.042	0.049	0.139	0.173
	Granular Residual	0.000	-0.004	0.000	0.005	0.007		0.000	0.000	0.000	0.001	0.002		0.000	-0.003	0.001	0.004	0.009
	Annual Number of Firms	52.865	40	53	63	13.18		20.241	17	20	25	4.84		63.053	58	65	69	11.726
	Annual GDP Growth	0.016	-0.003	0.02	0.033	0.034		0.019	0.001	0.024	0.042	0.032		0.018	0.005	0.02	0.035	0.019
CA	Sale ($ Million)	1323	22	95	422	8377	ID	1211	56	291	1565	2283	ME	447	10	26	554	770
	Employees (in 1000)	4.892	0.151	0.528	2.36	17.788		6.763	0.437	1.396	6.9	11.591		3.137	0.045	0.522	4.383	5.368
	Annual Productivity Growth	0.04	-0.055	0.044	0.145	0.182		0.025	-0.094	0.031	0.156	0.195		0.054	-0.026	0.046	0.126	0.134
	Granular Residual	0.000	-0.001	0.000	0.002	0.003		-0.001	-0.009	0.000	0.008	0.017		0.000	0.000	0.000	0.000	0.005
	Annual Number of Firms	617.527	535	588	747	146.789		8.659	8	9	9	1.528		3.818	3	4	5	1.369
	Annual GDP Growth	0.017	0.007	0.017	0.033	0.026		0.016	-0.008	0.016	0.038	0.033		0.017	0.005	0.013	0.034	0.022
CO	Sale ($ Million)	741	8	44	422	2108	IL	2859	89	379	1697	8319	MI	4904	52	229	1425	21000
	Employees (in 1000)	3.349	0.05	0.261	1.749	8.547		16.433	0.721	2.4	10.214	46.691		25.815	0.492	2.207	10	97.006
	Annual Productivity Growth	0.042	-0.072	0.047	0.164	0.197		0.044	-0.022	0.05	0.118	0.146		0.044	-0.026	0.047	0.122	0.146
	Granular Residual	-0.002	-0.008	0.000	0.010	0.022		0.000	-0.003	0.000	0.002	0.006		0.001	-0.002	0.001	0.003	0.003
	Annual Number of Firms	116.264	98	115	130	20.048		185.916	176	192	207	35.421		93.874	89	102	105	22.766
	Annual GDP Growth	0.017	0	0.017	0.033	0.021		0.016	0.01	0.014	0.029	0.023		0.009	-0.013	0.015	0.034	0.04
CT	Sale ($ Million)	1406	38	208	1051	4520	IN	982	82	249	885	2425	MN	1377	17	70	464	5471
	Employees (in 1000)	8.857	0.312	1.6	6.072	25.754		4.63	0.65	2	5.4	7.31		7.379	0.128	0.482	3.242	27.818
	Annual Productivity Growth	0.045	-0.031	0.048	0.122	0.153		0.039	-0.035	0.044	0.118	0.152		0.047	-0.034	0.046	0.133	0.163
	Granular Residual	0.001	-0.002	0.003	0.009	0.016		0.001	-0.002	0.001	0.004	0.006		0.003	-0.007	0.000	0.009	0.019
	Annual Number of Firms	99.443	90	103	115	21.558		53.227	46	56	59	9.624		130.273	109	130	157	28.087
	Annual GDP Growth	0.024	0.005	0.02	0.046	0.028		0.016	-0.002	0.021	0.032	0.032		0.021	0	0.019	0.042	0.026
DE	Sale ($ Million)	3481	35	218	1708	8942	KS	1237	20	77	323	4610	MO	1843	78	386	1638	5861
	Employees (in 1000)	14.697	0.312	1.147	7.996	32.722		6.07	0.2	0.619	3.09	12.815		11.323	0.673	2.707	10	22.741
	Annual Productivity Growth	0.046	-0.018	0.052	0.126	0.154		0.041	-0.038	0.045	0.121	0.158		0.045	-0.029	0.045	0.124	0.147
	Granular Residual	0.002	-0.001	0.000	0.005	0.014		0.001	-0.002	-0.001	0.004	0.007		-0.001	-0.004	0.000	0.004	0.011
	Annual Number of Firms	12.391	11	13	14	2.754		24.034	21	25	27	4.609		65.537	61	68	74	11.762
	Annual GDP Growth	0.019	0.002	0.02	0.041	0.028		0.015	0.001	0.019	0.029	0.019		0.014	0.003	0.015	0.03	0.023

Table 1: **Summary Statistics – Continued**

State	Variable	Mean	P25	P50	P75	Std.	State	Mean	P25	P50	P75	Std.	State	Mean	P25	P50	P75	Std.
MS	Sale ($ Million)	372	27	171	403	549	NV	688	18	88	557	1706	SD	1446	52	136	406	3526
	Employees (in 1000)	2.313	0.193	1.347	3	2.91		5.807	0.14	1	5.122	12.564		4.412	0.622	1.008	1.63	9.63
	Annual Productivity Growth	0.04	-0.058	0.04	0.162	0.188		0.04	-0.062	0.036	0.152	0.191		0.04	-0.03	0.039	0.111	0.118
	Granular Residual	0.000	0.000	0.000	0.000	0.001		-0.002	-0.006	-0.001	0.008	0.017		0.000	0.000	0.000	0.000	0.000
	Annual Number of Firms	8.291	5	8	11	2.938		39.139	32	38	48	10.868		3.638	3	3	4	0.98
	Annual GDP Growth	0.016	0.007	0.017	0.027	0.021		0.004	-0.011	0.011	0.024	0.035		0.027	0.008	0.027	0.045	0.029
MT	Sale ($ Million)	106	4	11	120	206	NY	1632	18	88	515	7192	TN	2179	113	397	1303	5760
	Employees (in 1000)	0.514	0.049	0.166	0.767	0.682		8.409	0.167	0.67	3.67	30.601		16.909	1.261	4	13	39.059
	Annual Productivity Growth	0.058	-0.073	0.052	0.201	0.194		0.044	-0.038	0.049	0.135	0.168		0.044	-0.022	0.043	0.118	0.139
	Granular Residual	0.000	0.000	0.000	0.000	0.002		0.002	-0.003	0.001	0.005	0.005		0.001	-0.003	0.000	0.004	0.007
	Annual Number of Firms	4.664	3	5	6	1.673		385.799	343	391	421	91.512		56.736	46	56	68	12.076
	Annual GDP Growth	0.012	-0.001	0.017	0.026	0.021		0.019	0.007	0.022	0.031	0.02		0.017	0.002	0.019	0.032	0.025
NC	Sale ($ Million)	1340	53	276	1161	4003	OH	2037	87	348	1231	8217	TX	2452	39	190	830	14000
	Employees (in 1000)	8.298	0.589	2.5	8.132	20.145		11.415	0.75	2.8	8.637	28.591		7.723	0.196	1.136	4.5	21.886
	Annual Productivity Growth	0.043	-0.027	0.042	0.117	0.147		0.042	-0.026	0.045	0.117	0.141		0.044	-0.054	0.048	0.149	0.182
	Granular Residual	0.000	-0.004	-0.001	0.002	0.004		0.001	-0.003	0.000	0.005	0.007		0.002	-0.003	0.003	0.007	0.011
	Annual Number of Firms	81.892	76	84	91	12.236		157.64	135	171	179	33.039		386.659	338	381	433	65.239
	Annual GDP Growth	0.017	0.005	0.016	0.035	0.024		0.017	0.008	0.018	0.034	0.027		0.015	0.003	0.019	0.03	0.024
ND	Sale ($ Million)	180	5	10	61	457	OK	693	14	70	488	1903	UT	692	10	45	257	2482
	Employees (in 1000)	0.441	0.022	0.15	0.399	0.709		1.693	0.079	0.422	1.821	3.057		3.864	0.064	0.319	1.4	16.21
	Annual Productivity Growth	0.033	-0.047	0.046	0.142	0.168		0.046	-0.061	0.054	0.162	0.194		0.035	-0.056	0.039	0.13	0.182
	Granular Residual	0.000	0.000	0.000	0.000	0.001		-0.001	-0.009	-0.002	0.007	0.020		-0.003	-0.005	0.000	0.003	0.020
	Annual Number of Firms	3.469	2	4	4	1.341		36.51	32	37	40	6.028		36.641	32	37	44	9.199
	Annual GDP Growth	0.021	-0.017	0.018	0.058	0.055		0.013	0.01	0.018	0.026	0.027		0.019	0.005	0.023	0.038	0.026
NE	Sale ($ Million)	2295	34	303	1524	5123	OR	769	30	150	588	2584	VA	2057	48	253	1152	6601
	Employees (in 1000)	10.1	0.283	1.53	10.657	18.128		3.405	0.243	0.885	3.1	6.997		10.048	0.432	1.814	7.5	22.761
	Annual Productivity Growth	0.047	-0.023	0.047	0.118	0.132		0.043	-0.04	0.05	0.144	0.171		0.043	-0.032	0.049	0.121	0.154
	Granular Residual	0.005	-0.003	0.002	0.013	0.017		0.000	-0.002	0.000	0.002	0.008		0.000	-0.003	0.001	0.005	0.006
	Annual Number of Firms	15.56	12	17	19	4.242		39.117	30	36	47	11.774		105.759	92	104	119	20.79
	Annual GDP Growth	0.02	0.008	0.017	0.028	0.021		0.027	0.013	0.026	0.043	0.034		0.017	0.002	0.016	0.03	0.018
NH	Sale ($ Million)	349	21	120	440	579	PA	1527	37	190	984	5975	VT	334	13	43	132	912
	Employees (in 1000)	2.326	0.175	0.957	3.834	3.165		7.798	0.322	1.504	6.3	19.625		1.184	0.113	0.4	1.15	1.906
	Annual Productivity Growth	0.043	-0.036	0.043	0.132	0.171		0.049	-0.025	0.051	0.129	0.156		0.045	-0.037	0.064	0.153	0.181
	Granular Residual	0.000	-0.002	0.000	0.001	0.006		0.000	-0.004	0.000	0.004	0.008		-0.003	0.000	0.000	0.000	0.010
	Annual Number of Firms	19.295	16	20	23	5.631		176.096	166	179	197	34.608		4.526	4	5	5	1.52
	Annual GDP Growth	0.026	0.007	0.029	0.046	0.032		0.017	0.01	0.017	0.028	0.019		0.026	0.012	0.031	0.039	0.026
NJ	Sale ($ Million)	1367	12	63	418	5516	RI	4626	39	176	1888	19000	WA	2735	30	168	774	12000
	Employees (in 1000)	7.704	0.11	0.538	3	31.594		15.867	0.292	1.768	7	39.313		9.583	0.221	0.911	4.1	30.819
	Annual Productivity Growth	0.047	-0.042	0.052	0.141	0.173		0.043	-0.016	0.048	0.12	0.149		0.044	-0.035	0.043	0.138	0.17
	Granular Residual	0.002	-0.003	0.001	0.006	0.009		0.001	-0.008	-0.002	0.009	0.025		0.001	-0.001	0.000	0.004	0.005
	Annual Number of Firms	219.484	215	233	247	44.411		13.844	12	14	16	2.931		64.915	52	62	80	17.647
	Annual GDP Growth	0.02	0.004	0.016	0.037	0.023		0.018	0.006	0.025	0.031	0.022		0.014	-0.001	0.015	0.031	0.023
NM	Sale ($ Million)	71	2	8	42	223	SC	688	60	270	696	1075	WI	1275	77	280	1032	3460
	Employees (in 1000)	1.082	0.026	0.078	0.4	4.781		9.217	0.467	2.875	9.622	18.808		7.141	0.705	2.299	6.8	17.732
	Annual Productivity Growth	0.03	-0.103	0.049	0.18	0.226		0.044	-0.024	0.045	0.119	0.138		0.043	-0.022	0.046	0.113	0.136
	Granular Residual	0.000	0.000	0.000	0.000	0.001		0.000	-0.002	0.000	0.001	0.003		-0.001	-0.003	0.000	0.002	0.005
	Annual Number of Firms	5.671	5	6	7	1.711		21.489	19	23	26	5.179		65.054	59	67	73	10.612
	Annual GDP Growth	0.018	-0.011	0.013	0.028	0.034		0.019	0.009	0.019	0.028	0.024		0.018	0.011	0.019	0.03	0.02
WV	Sale ($ Million)	297	10	117	424	443	WY	140	3	9	88	357	Total	1696	28	145	718	9132
	Employees (in 1000)	1.609	0.098	0.74	2.95	1.864		0.463	0.035	0.215	0.929	0.541		8.453	0.217	1.035	4.651	36.644
	Annual Productivity Growth	0.042	-0.034	0.046	0.126	0.153		0.057	-0.069	0.062	0.146	0.186		0.043	-0.039	0.047	0.133	0.167
	Granular Residual	0.000	-0.001	0.000	0.001	0.002		0.000	0.000	0.000	0.000	0.001		0.000	-0.002	0.000	0.003	0.010
	Annual Number of Firms	5.814	5	6	7	1.78		3.205	3	3	3	1.471		242.844	89	178	370	204.471
	Annual GDP Growth	0.013	-0.003	0.015	0.024	0.025		0.017	0.003	0.019	0.039	0.039		0.017	0.005	0.018	0.032	0.025

Table 2: **Identification of Granular States**

This table shows states in which productivity shocks to locally dominant firms explain over 8% of the state's GDP growth. States are ranked based on the estimated R^2 from time-series regressions with states' GDP growth as the dependent variable (Regression (5)). Γ_t and Γ_{t-1} are the independent variables, and are equal to the granular residual of locally dominant firms at time t and $t-1$, respectively (Equation (4)). Locally dominant firms per state are defined as firms that, after excluding the top-100 U.S. firms, are in the top quartile of the state's size distribution, where size is the prior year's net firm sales. A state GDP growth is the log change of the state's real GDP per capita (Equation (1)). To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

State	Γ_t	Γ_{t-1}	R^2 (%)	Average GDP Growth (%)	State	Γ_t	Γ_{t-1}	R^2 (%)	Average GDP Growth (%)
CA	0.387	0.359	28.5	1.6	IN	0.375	-0.165	12.8	1.5
	(3.52)	(3.47)				(1.84)	(-0.99)		
VT	0.491	-0.260	21.7	2.3	OK	0.185	0.379	12.2	1.3
	(9.68)	(-2.73)				(0.87)	(1.78)		
FL	0.408	0.181	21.3	1.2	NJ	0.229	0.377	11.8	1.8
	(2.05)	(2.02)				(1.41)	(2.98)		
MS	0.418	0.009	17.7	1.5	NV	0.308	0.091	10.9	0.4
	(2.79)	(0.08)				(3.90)	(0.58)		
AL	0.085	0.354	16.2	1.6	NM	0.214	0.385	9.8	1.3
	(0.54)	(2.32)				(1.21)	(1.97)		
AZ	0.173	0.352	16.1	1.4	TX	0.007	0.302	8.7	1.4
	(1.22)	(1.77)				(0.03)	(1.75)		
WI	0.073	0.370	13.1	1.6					
	(0.74)	(2.34)							

Table 3: **Summary Statistics of Granular States**
This table shows the summary statistics of firms headquartered in the granular states. Column (1) shows the granular states, identified in Table 2. Columns (2) and (5) show the annual average number of locally dominant and non-dominant firms per state. Columns (3) and (6) show the annual average of firms' net sales. Columns (4) and (7) show the annual average of firms' number of employees. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's size distribution, where size is the prior year's net firm sales. Sales data are in million U.S. dollars, and employee numbers are in thousands. Firm data are from Compustat. The sample period is from 1977 to 2017.

	Panel A: Locally Dominant Firms			Panel B: Non-Dominant Firms		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
State	Number of Firms	Sales	Employees	Number of Firms	Sales	Employees
AL	6.22	1637.27	11.61	16.41	185.01	1.71
AZ	16.15	2510.73	11.21	43.53	164.44	1.21
CA	179.67	1598.03	9.43	513.51	74.60	0.45
FL	56.30	1878.23	14.49	157.43	70.10	0.59
IN	14.82	2425.78	10.88	41.75	244.53	1.75
MS	3.11	680.63	4.17	6.70	121.65	0.98
NJ	59.94	1997.57	13.68	173.00	55.01	0.48
NM	2.41	164.50	2.42	4.68	6.92	0.07
NV	14.20	1416.00	12.52	31.84	61.69	0.56
OK	11.45	1771.13	3.92	30.45	113.04	0.44
TX	107.14	2546.60	12.35	306.81	155.04	1.04
VT	1.88	498.33	2.04	3.20	25.97	0.26
WI	17.55	2602.30	13.77	49.85	289.68	2.00

Table 4: **Persistence of Locally Dominant Firms Across Time**
This table shows the result of Run's (1968) test. For each potential locally dominant firm in the granular states, we create a sequence of ones and zeros, where ones represent instances that the firm is among the locally dominant firms and zeros otherwise. Using this sequence, we measure a z statistic (Equation (6)) for each locally dominant firm. Firms with an absolute z score above 1.96 are identified as firms with a non-random turnover. Column (1) shows the granular states, identified in Table 2. Column (2) shows the number of locally dominant firms in each state. Column (3) shows the number of locally dominant firm with a non-random turnover. Column (4) shows the average z score for all possible locally dominant firms per state. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's size distribution, where size is the prior year's net firm sales. Firm data are from Compustat. The sample period is from 1977 to 2017.

(1) State	(2) Total Number of Locally Dominant Firms	(3) Number of Non-Random Dominant Firms	(4) Average z Score
AL	24	20	4.64
AZ	61	59	5.22
CA	762	669	4.87
FL	238	208	4.75
IN	57	51	5.05
MS	18	13	3.54
NJ	236	212	4.98
NM	22	15	3.12
NV	67	58	4.50
OK	54	44	4.26
TX	448	388	4.76
VT	11	8	3.91
WI	57	52	5.01
Average	158.08	138.23	4.51

Table 5: **Locally Dominant Firms and Division/Regional GDP Growth**
This table shows the economic impact of locally dominant firms in a granular state on the GDP growth of the state's division and regional areas. To identify the economic power of locally dominant firms in a granular state, the state's division (or regional) GDP growth is regressed on the granular residual of the locally dominant firms. Division areas are defined based on the U.S. Census categories. A state's regional area is defined as a group of states that share a border with the state. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. Granular states are identified in Table 2. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

Panel A: Division Level				Panel B: Regional Level			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State	Γ_t	Γ_{t-1}	R^2 (%)	State	Γ_t	Γ_{t-1}	R^2 (%)
CA	0.426	0.351	31.0	CA	0.010	0.009	30.5
	(3.73)	(3.57)			(3.83)	(3.52)	
FL	0.417	0.178	20.4	FL	0.011	0.004	25.3
	(3.02)	(2.23)			(2.75)	(2.02)	
IN	0.447	-0.184	18.1	NV	0.010	0.007	25.3
	(2.42)	(-1.27)			(3.52)	(2.21)	
VT	0.436	-0.122	16.0	VT	0.010	-0.002	23.0
	(9.09)	(-3.06)			(9.21)	(-1.14)	
NJ	0.208	0.388	15.0	AL	0.006	0.005	18.7
	(1.37)	(4.13)			(1.91)	(1.86)	
OK	0.324	0.297	14.2	IN	0.012	-0.005	18.0
	(1.62)	(1.78)			(2.38)	(-1.29)	
AL	0.196	0.236	13.5	OK	0.007	0.007	17.1
	(1.06)	(1.52)			(1.87)	(2.13)	
MS	0.337	-0.0813	12.2	MS	0.008	-0.0004	16.2
	(2.01)	(-0.85)			(2.61)	(-0.21)	
AZ	0.174	0.257	10.5	NJ	0.004	0.007	15.3
	(1.36)	(1.26)			(1.41)	(4.38)	
TX	0.0690	0.339	10.4	AZ	0.004	0.007	14.3
	(0.38)	(2.07)			(1.64)	(1.59)	
WI	0.0455	0.290	8.2	TX	0.002	0.007	9.4
	(0.51)	(1.64)			(0.39)	(1.98)	

Table 6: **Locally Dominant Firms and U.S. GDP Growth**

This table presents the estimates of times-series regressions, where the U.S. GDP growth is the dependent variable. Column (1) shows the economic significance of shocks to the nationally large firms, where $\Gamma_{top100,t}$ is the granular residual of the top-100 U.S. firms at time t. Column (2) repeats the same analysis but focuses on the significance of shocks to locally dominant firms, where $\Gamma_{dom,t}$ is the granular residual of locally dominant firms in the granular states at time t. Column (3) shows the cumulative effects of nationally dominant and locally dominant firms on the U.S. GDP growth. The nationally dominant firms are the 100 largest firms in the United States. Locally dominant firms in each granular state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. Granular states are identified in Table 2. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

	(1) Top-100 Firms	(2) Locally Dominant Firms	(3) (1)+(2)
$\Gamma_{top100,t}$	0.502		0.233
	(3.01)		(1.52)
$\Gamma_{top100,t-1}$	0.261		0.147
	(2.34)		(1.38)
$\Gamma_{dom,t}$		0.663	0.570
		(4.75)	(4.05)
$\Gamma_{dom,t-1}$		0.295	0.242
		(2.58)	(1.57)
R^2 (%)	24.2	47.8	52.4
Adj. R^2 (%)	19.8	44.8	46.4

Table 7: **Aggregate Impact of Granular States: Mechanism**

This table repeats the analysis of Table 6, but uses a weighted average of shocks to locally dominant firms as the main independent variable. In Column (1), we use the estimated R^2 in Table 2 to create a weighted average granular residual of locally dominant firms as the main independent variable (i.e., Γ_{dom}). Column (2) shows the cumulative effects of shocks to the top-100 U.S. firm and locally dominant firms (in Column (1)) on the U.S. GDP growth. Columns (3) and (5) use the estimated R^2 in Table 5 to create a weighted average granular residual of locally dominant firms as the main independent variable. Column (4) (Column (6)) shows the cumulative effects of shocks to the top-100 U.S. firm and locally dominant firms in Column (3) (Column (5)) on the U.S. GDP growth. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

	Panel A: State-Level Granularity		Panel B: Division-Level Granularity		Panel C: Regional-Level Granularity	
	(1)	(2)	(3)	(4)	(5)	(6)
	Locally Dominant Firms	Top-100 U.S. Firms + Locally Dominant Firms	Locally Dominant Firms	Top-100 U.S. Firms + Locally Dominant Firms	Locally Dominant	Top-100 U.S. Firms + Locally Dominant Firms
$\Gamma_{top100,t}$		0.264		0.271		0.253
		(1.78)		(1.78)		(1.77)
$\Gamma_{top100,t-1}$		0.272		0.246		0.265
		(2.34)		(2.10)		(2.30)
$\Gamma_{dom,t}$	0.564	0.569	0.567	0.551	0.590	0.566
	(4.50)	(3.86)	(4.49)	(3.87)	(4.74)	(3.94)
$\Gamma_{dom,t-1}$	0.393	0.263	0.380	0.269	0.368	0.247
	(3.23)	(2.23)	(3.24)	(2.27)	(3.26)	(2.18)
R^2 (%)	53.9	62.2	52.9	60.9	55.6	62.2
Adj. R^2 (%)	51.1	57.4	50.2	56.1	53.1	67.5

Appendices

to accompany

This Appendix presents a set of supplementary tests that support the main analyses in the paper. The order of the items in this Appendix follows that of the main text.

Table A1: **Pearson Correlations**

This table presents the Pearson correlation coefficients between the main variable of interests. To compute the correlations we pool all the data across all the states. Panel A reports estimates based on the sample of all states. Panel B restricts the sample only to the granular states (i.e., California, Vermont, Florida, Mississippi, Alabama, Arizona, Wisconsin, Indiana, Oklahoma, New Jersey, Nevada, New Mexico, and Texas). Γ_t is the granular residual measure (Equation (4)). *GDP Growth* is the log change of state's real GDP per capita. Correlations that are significant at least at the 5% level confidence are shown in bold text. The sample period is from 1977 to 2017.

Panel A: All States				
	(1)	(2)	(3)	(4)
	Γ_t	Γ_{t-1}	Γ_{t-2}	$GDP\ Growth_t$
Γ_t	1			
Γ_{t-1}	**-0.072**	1		
Γ_{t-2}	**-0.068**	**-0.070**	1	
$GDP\ Growth_t$	**0.046**	**0.048**	0.016	1
Panel B: Granular States				
Γ_t	1			
Γ_{t-1}	**-0.097**	1		
Γ_{t-2}	0.000	**-0.097**	1	
$GDP\ Growth_t$	**0.172**	**0.173**	-0.037	1

Table A2: **Locally Dominant Firms in the Granular States: Examples**

This table provides examples of the locally dominant firms in the granular states in a random year (2001). Panel A lists (up to) 5 locally dominant firms per granular state in 2001. Panel B shows the top-10 largest firms in the U.S. in 2001. Granular states are identified in Table 2. Sales data are in million U.S. dollars. Firm data are from the Compustat database.

Panel A: Top-5 Locally Dominant Firms in the Granular States in 2001

Company's Name	HQ State	Sales	Company's Name	HQ State	Sales
INTERGRAPH CORP	AL	532	TRANE INC	NJ	7,465
WOLVERINE TUBE INC	AL	583	AVIS BUDGET GROUP INC	NJ	8,613
BIRMINGHAM STEEL CORP	AL	700	SCHERING-PLOUGH	NJ	9,802
WALTER ENERGY INC	AL	1,910	GREAT ATLANTIC & PAC TEA CO	NJ	10,623
VULCAN MATERIALS CO	AL	3,020	TOYS R US INC	NJ	11,332
INSIGHT ENTERPRISES INC	AZ	2,082	RESERVE INDUSTRIES CORP	NM	2
SWIFT TRANSPORTATION CO INC	AZ	2,112	SBS TECHNOLOGIES INC	NM	187
PETSMART INC	AZ	2,224			
PHELPS DODGE CORP	AZ	4,002	INTL GAME TECHNOLOGY	NV	1,199
AVNET INC	AZ	12,814	AMERCO	NV	1,814
			CAESARS ENTERTAINMENT CORP	NV	3,709
AVAYA INC	CA	6,793	MGM RESORTS INTERNATIONAL	NV	3,973
APPLIED MATERIALS INC	CA	7,343	CAESARS ENTERTAINMENT INC	NV	4,631
AGILENT TECHNOLOGIES INC	CA	8,396			
ORACLE CORP	CA	10,860	DOLLAR THRIFTY AUTOMOTIVE GP	OK	1,020
FLEXTRONICS INTERNATIONAL	CA	12,110	WILTEL COMMUNICATIONS GROUP	OK	1,186
			DEVON ENERGY CORP	OK	3,045
RYDER SYSTEM INC	FL	5,006	KERR-MCGEE CORP	OK	3,638
LENNAR CORP	FL	6,002	YORK INTERNATIONAL CORP	OK	3,931
CSX TRANSPORTATION INC	FL	6,196			
CSX CORP	FL	8,110	FLUOR CORP	TX	8,972
OFFICE DEPOT INC	FL	11,154	BNSF RAILWAY CO	TX	9,169
			BURLINGTON NORTHERN SANTA FE	TX	9,176
HILL-ROM HOLDINGS INC	IN	2,131	TENET HEALTHCARE CORP	TX	12,053
NATIONAL WINE & SPIRITS INC	IN	2,492	HALLIBURTON CO	TX	12,939
NATIONAL STEEL CORP -CL B	IN	2,492			
GUIDANT CORP	IN	2,708	KEURIG GREEN MOUNTAIN INC	VT	96
CUMMINS INC	IN	5,681	IDX SYSTEMS CORP	VT	380
CAL-MAINE FOODS INC	MS	358	SHOPKO STORES INC	WI	3,531
HANCOCK FABRICS INC	MS	385	HARLEY-DAVIDSON INC	WI	3,545
SANDERSON FARMS INC	MS	706	ROCKWELL AUTOMATION	WI	4,279
WELLMAN INC	MS	1,081	KOHL'S CORP	WI	6,152
			MANPOWERGROUP	WI	10,484

Panel B: Top-10 Nationally Dominant Firms in the U.S. in 2001

Company's Name	HQ State	Sales
KROGER CO	OH	49,000
AT&T CORP	NJ	52,550
BOEING CO	IL	58,198
VERIZON COMMUNICATIONS INC	NY	67,190
ALTRIA GROUP INC	VA	72,944
INTL BUSINESS MACHINES CORP	NY	85,866
CHEVRON CORP	CA	97,863
FORD MOTOR CO	MI	162,412
GENERAL MOTORS CO	MI	175,353
WAL-MART STORES INC	AR	192,003

Table A3: **Aggregate Impact of Granular States: Mechanism**

This table repeats the same analysis of Table 7, but exclude granular states with the highest number of locally dominant firms (i.e., CA, TX, FL, and NJ). To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

	Panel A: State-Level Granularity		Panel B: Division-Level Granularity		Panel C: Regional-Level Granularity	
	(1)	(2)	(3)	(4)	(5)	(6)
	Locally Dominant Firms	Top-100 U.S. Firms + Locally Dominant Firms	Locally Dominant Firms	Top-100 U.S. Firms + Locally Dominant Firms	Locally Dominant	Top-100 U.S. Firms + Locally Dominant Firms
$\Gamma_{top100,t}$		0.280		0.235		0.235
		(2.38)		(2.14)		(2.09)
$\Gamma_{top100,t-1}$		0.390		0.307		0.359
		(3.19)		(2.51)		(2.90)
$\Gamma_{dom,t}$	0.603	0.636	0.671	0.647	0.662	0.652
	(4.30)	(5.13)	(5.23)	(5.61)	(4.73)	(5.19)
$\Gamma_{dom,t-1}$	0.285	0.115	0.227	0.100	0.280	0.096
	(1.92)	(0.87)	(2.12)	(0.99)	(2.08)	(0.71)
R^2 (%)	44.7	58.2	50.4	59.4	47.7	56.9
Adj. R^2 (%)	41.5	53.0	47.5	54.3	44.8	51.5

Table A4: **Economic Relevance of Locally Dominant Firms for Their HQ States**
This table repeats the analysis of Table 2, but focuses on the locally dominant firms that are economically important in their HQ states (Panel A) and locally dominant firms with no international sales (Panel B). In Panel A, we define a firm as economically important, if its HQ state is among the top three most-cited states in the firm's annual 10-K filings. In Panel B, we use the geographical segment of the Compustat database to identify firms with no international sales. Column (1) shows the granular states, identified in Table 2. Column (2) shows the total number of locally dominant firms in each granular state. Column (3) in Panel A (Panel B) shows the total number of locally dominant firms that are economically important in their HQ states (have no international sales). Column (4) shows the estimated R^2 from Regression (5), with the sample of locally dominant firms identified in Column (3). Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. Firm data are from Compustat. Real GDP per capita information is from the BEA. The information about state exposure of firms is from Bernile et al. (2020). The sample period is from 1994 to 2012 in Panel A, and from 1977 to 2017 in Panel B.

Panel A: Annual 10-K Data			
(1) Granular States	(2) Number of Dominant Firms	(3) Economically Important Dominant Firms	(4) Estimated R^2 (%) with Firms in Column (3)
CA	468	217	10.0
FL	118	52	18.3
VT	6	3	22.2
MS	20	10	9.7
AZ	40	17	12.6
IN	44	19	36.9
AL	15	7	21.4
OK	25	7	68.7
NJ	96	35	11.8
NV	36	16	23.6
Panel B: International Sales Data			
(1) Granular States	(2) Number of Dominant Firms	(3) Dominant Firms with No International Sales	(4) Estimated R^2 (%) with Firms in Column (3)
CA	593	265	5.80
FL	180	131	15.00
VT	6	4	12.60
MS	10	7	12.00
AZ	50	28	6.20
IN	40	23	19.70
OK	36	25	30.00
NV	54	46	17.70
NM	11	10	18.40
TX	340	212	22.70

Table A5: **Alternative Measure of Idiosyncratic Shocks**

This table repeats the analysis of Table 2, but uses alternative methods to measure firm-level productivity shocks. Panel A uses the estimated residual from Regression (12) to measure firms' idiosyncratic productivity shocks. Column (1) of Panel A shows the granular states, for which the estimated R^2 in Column (2) is above 8%. In Column (2) we use a weighted average of shocks to locally dominant firms (based on lagged net sales) to measure granular residual. In Column (3) of Panel A, we repeat the same analysis of Column (2), but we assign equal weights to productivity shocks. Panel B uses 3- and 2-digits SIC codes to measure common-industry shocks. Panel C uses PCA to identify common shocks that jointly explain the variations in state GDP growth and those of firms' productivity growth (Equations 13 and 14). Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017.

Panel A: Residual Method		
(1) State	(2) Estimated R^2 (%) Weighted Average Shocks	(3) Estimated R^2 (%) Unweighted Average Shocks
CA	9.7	15.8
VT	18.2	4.3
MS	8.1	12.4
IN	10.2	9.0
OK	17.6	6.6
NJ	16.0	19.7
TX	19.4	17.9

Panel B: Industry De-Meaning Method		
(1) State	(2) Estimated R^2 (%) SIC-3 Demeaning	(3) Estimated R^2 (%) SIC-2 Demeaning
CA	4.4	5.4
VT	5.2	11.9
MS	7.2	8.7
AL	6.6	4.3
FL	5.1	6.7
IN	10.5	35.3
TX	2.9	5.0
OK	3.7	7.4
AZ	12.8	27.5
NJ	12.8	8.6

Table A5: **Alternative Measure of Idiosyncratic Shocks (cont'd)**

Panel C: PCA Method

(1) State	(2) Estimated R^2 (%)	(3) Granular	(4) Estimated R^2 (%)
CA	27.3	IN	14.9
VT	8.3	NV	11.4
MS	14.4	NM	11.3
AL	28.0	TX	5.4
FL	13.5	OK	5.5
WI	22.7		

Table A6: **Expanding the Sample Size of Locally Dominant Firms**
Panel A (Panel B) repeats the same analysis of Table 2 (Table 6), but expands the sample of locally dominant firms to firms that, after excluding the top-100 U.S. firms, are among the top-tercile of size distribution in their HQ states, where size is the prior year's net firm sales. $\Gamma_{dom,t}$ and $\Gamma_{top100,t}$ shows the granular residual of locally dominant and top-100 U.S. firms, respectively. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017. t-statistics are reported in parentheses below the coefficient estimates.

Panel A: State-Level Regression

State	Γ_t	Γ_{t-1}	R^2 (%)	State	Γ_t	Γ_{t-1}	R^2 (%)
CA	0.359	0.298	18.7	NM	-0.214	-0.335	8.4
	(3.01)	(2.35)			(-0.74)	(-1.49)	
VT	0.494	-0.267	22.6	TX	-0.052	0.283	8.9
	(9.45)	(-2.89)			(-0.25)	(1.96)	
MS	0.378	0.0232	13.9	OK	0.135	0.308	7.8
	(2.41)	(0.21)			(0.59)	(2.12)	
AL	-0.050	0.330	9.9	WI	0.087	0.367	10.7
	(-0.19)	(2.34)			(0.93)	(2.07)	
FL	0.35	0.088	14.6	AZ	0.336	0.239	20.9
	(1.67)	(0.76)			(2.94)	(1.47)	
NJ	0.123	0.305	9.1	IN	0.479	-0.230	25.6
	(0.69)	(2.23)			(2.49)	(-1.44)	
NV	0.373	0.402	24.6	NM	-0.214	-0.335	8.4
	(2.62)	(1.59)			(-0.74)	(-1.49)	

Panel B: National-Level Regression

$\Gamma_{dom,t}$	0.503	0.436
	(3.61)	(4.01)
$\Gamma_{dom,t-1}$	0.386	0.321
	(3.21)	(2.87)
$\Gamma_{top100,t}$		0.312
		(2.32)
$\Gamma_{top100,t-1}$		0.172
		(1.57)
R^2 (%)	44.6	53.1
Adj. R^2 (%)	41.4	47.3

Table A7: **Effects of Large Productivity Shocks**

This table winsorizes demeaned productivity shocks (Equation (3)) to identify the impact of shocks to locally dominant firms in granular states. Table 2 identifies granular states. Demeaned productivity shocks are winsorized at +/-5% in Columns 2 and 6, +/-10% in Columns 3 and 7, and +/-20% in Columns 4 and 8. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017.

(1) State	(2) R^2 (%) 5% Winsor.	(3) R^2 (%) 10% Winsor.	(4) R^2 (%) 20% Winsor.	(5) State	(6) R^2 (%) 5% Winsor.	(7) R^2 (%) 10% Winsor.	(8) R^2 (%) 20% Winsor.
CA	31.90	23.70	12.90	NM	7.00	6.80	4.20
VT	21.80	19.40	15.20	TX	18.50	17.40	13.30
MS	14.40	7.70	7.30	OK	11.50	10.00	9.30
AL	18.30	24.60	28.30	WI	8.30	9.00	10.70
FL	11.50	8.00	6.00	AZ	16.60	18.30	19.80
NJ	22.70	22.40	17.70	IN	0.50	0.60	2.50
NV	10.30	8.50	5.80				

Table A8: **Summary of Robustness Tests**

This table provides a summary of the estimated R^2 from Table 2 (Column 2), Table A5 (Column 3), Table A4 (Column 4), Table A7 (Columns 5 to 7), Table A6 (Column 8), along with the average R^2 from these robustness methods in Column (9). Columns (10) and (11) show the ranking of the granular states based on the estimated R^2 in Columns (2) and (9), respectively. Granular states are identified in Table 2. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
State	Baseline	Industry Shocks	International Sales	Winsorize 5%	Winsorize 10%	Winsorize 20%	Top tercile	Average R^2	State Rank (Column 2)	State Rank (Column 9)
CA	28.5	4.4	5.8	31.9	23.7	12.9	18.7	18.0	1	1
FL	21.3	5.1	15.0	11.5	8.0	6.0	14.6	11.6	2	2
VT	21.7	5.2	12.6	21.8	19.4	15.2	22.6	16.9	3	8
MS	17.7	7.2	12.0	14.4	7.7	7.3	13.9	11.5	4	9
AL	16.2	6.6	0.5	18.3	24.6	28.3	9.9	14.9	5	4
AZ	16.1	12.8	6.2	16.6	18.3	19.8	20.9	15.8	6	3
WI	13.1	4.4	4.0	8.3	9.0	10.7	10.7	8.6	7	12
IN	12.8	10.5	19.7	0.5	0.6	2.5	25.6	10.3	8	11
OK	12.2	3.7	30.0	11.5	10.0	9.3	7.8	12.1	9	7
NJ	11.8	12.8	2.1	22.7	22.4	17.7	9.1	14.1	10	5
NV	10.9	0.5	17.7	10.3	8.5	5.8	24.6	11.2	11	10
NM	9.8	1.1	18.4	7.0	6.8	4.2	8.40	8.0	12	13
TX	8.7	2.9	22.7	18.5	17.4	13.3	8.9	13.2	13	6

Table A9: **Impact of Locally Dominant Firms Beyond other Shocks**
This table repeats the analysis of Table 6 but additionally controls for oil and monetary shocks as well as the interest rate and term spread. *Oil* shows Hamilton's (2003) oil shock, while *Monetary* shows Romer and Romer's (2004) monetary shock. $\Gamma_{dom,t}$ and $\Gamma_{top100,t}$ shows the granular residual of locally dominant and top-100 U.S. firms, respectively. r shows the interest rate. *Term Spread* is the difference between 10-year and 1-year treasury constant maturity rate. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Real and nominal GDP per capita information is from the BEA. Oil and monetary shock data are from Gabaix (2011). Interest rate information is from Kenneth R. French website. Term spread information is from FRED. t-statistics are reported in parentheses below the coefficient estimates. The sample period is from 1977 to 2000.

	Dependent Variable: U.S. GDP Growth (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Oil (t)	-0.025		0.009		-0.186			0.016
	(-0.16)		(0.05)		(-0.90)			(0.04)
Oil (t-1)	-0.334		-0.319		-0.472			-0.128
	(-2.32)		(-2.07)		(-1.92)			(-0.40)
Oil (t-2)	-0.473		-0.481		-0.301			-0.004
	(-2.34)		(-2.50)		(-1.40)			(-0.01)
Monetary (t)		-0.294	-0.31		-0.101			-0.139
		(-1.18)	(-1.41)		(-0.62)			(-0.67)
Monetary (t-1)		0.049	0.106		0.307			0.276
		(0.22)	(0.55)		(1.66)			(0.87)
Monetary (t-2)		-0.242	-0.135		0.206			0.235
		(-0.99)	(-0.59)		(1.12)			(0.85)
$\Gamma_{dom,t}$				0.626	0.465		0.619	0.605
				(2.13)	(1.79)		(2.09)	(1.55)
$\Gamma_{dom,t-1}$				0.249	0.409		0.411	0.621
				(1.05)	(1.37)		(2.08)	(2.19)
$\Gamma_{top100,t}$				0.292	0.176		0.286	0.21
				(1.68)	(0.77)		(0.96)	(0.71)
$\Gamma_{top100,t-1}$				0.315	0.354		0.476	0.529
				(1.65)	(1.69)		(2.00)	(0.99)
Term Spread (t)						0.245	0.416	0.272
						(0.60)	(0.88)	(0.42)
Term Spread (t-1)						-0.362	-0.236	-0.268
						(-0.79)	(-0.33)	(-0.35)
Term Spread (t-2)						0.384	0.58	0.745
						(1.38)	(1.60)	(1.28)
r (t)						0.935	0.557	0.242
						(1.64)	(1.15)	(0.26)
r (t1)						-1.815	-0.667	-0.535
						(-3.03)	(-0.82)	(-0.66)
r (t-2)						0.870	0.729	0.955
						(2.14)	(1.24)	(1.35)
R^2 (%)	25.1	10.8	34.0	46.3	69.8	46.5	73.0	0.865
Adj. R^2 (%)	13.2	-3.2	9.3	33.6	42.4	26.4	48.4	0.432
Joint F-test				6.26	5.80		13.39	5.01
$\Gamma_{dom,t}$ and $\Gamma_{dom,t-1}$								
p-value of F-test				0.009	0.019		0.001	0.064

Table A10: **Only Top-100 Locally Dominant Firms**

This table repeats the analysis of Table 6 with some modifications. In Column (1), we restrict the sample of locally dominant firms to the top-100 largest firms to create the granular residual (i.e., $\Gamma_{dom,t}$). Column (2) shows the cumulative effect of shocks to the top-100 U.S. firms and the top-100 locally dominant firms on the U.S. GDP growth. Column (3) repeats the same analysis as in Column (3) of Table 6, but uses the U.S. nominal GDP per capita growth as the dependent variable. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Real and nominal GDP per capita information is from the BEA. We use the U.S. population data available on FRED, to measure nominal GDP per capita. The sample period is from 1977 to 2017 in Columns (1) and (2). The sample period is from 1963 to 2017 in Column (3). t-statistics are reported in parentheses below the coefficient estimates.

	(1) Top-100 Locally Dominant Firms	(2) Top-100 U.S. Firms+ Top-100 Locally dominant Firms	(3) Top-100 U.S. Firms+ Locally Dominant Firms
$\Gamma_{top100,t}$		0.291	0.334
		(1.88)	(3.34)
$\Gamma_{top100,t-1}$		0.142	0.269
		(1.37)	(2.34)
$\Gamma_{dom,t}$	0.633	0.519	0.304
	(4.23)	(3.80)	(2.94)
$\Gamma_{dom,t-1}$	0.282	0.250	0.267
	(2.26)	(1.59)	(3.10)
R^2 (%)	42.5	49.3	44.6
Adj. R^2 (%)	39.1	42.9	30.8
Sample Period	1977-2017	1977-2017	1963-2017

Table A11: **Alternative Measure of Productivity Growth**

This table repeats the analysis in Table 2, but uses firm-level TFP to measure productivity growth. Column (1) shows the granular states, identified in Table 2 for which the estimated R^2 is above 8%. Columns (2) and (3) show the granular residual of locally dominant firms at time t and $t-1$. Column (4) shows the estimated R^2 from Regression (5), using TFP as the main measure of firm-level productivity growth. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution, where size is the prior year's net firm sales. To facilitate the comparison across the estimated coefficients, we standardize all continuous variables to have a mean equal to 0 and a standard deviation equal to 1. Firm data are from Compustat. Real GDP per capita information is from the BEA. Firm-Level TFP data are from İmrohoroğlu and Tüzel (2014). The sample period is from 1977 to 2009. t-statistics are reported in parentheses below the coefficient estimates.

(1) States	(2) Γ_t	(3) Γ_{t-1}	(4) R^2 (%)
CA	0.541	0.153	30.4
	(4.08)	(1.14)	
VT	0.308	-0.195	13.5
	(2.20)	(-2.32)	
MS	-0.330	-0.051	9.9
	(-1.66)	(-0.33)	
AL	-0.009	0.278	8.0
	(-0.09)	(1.62)	
AZ	0.034	0.263	6.4
	(0.17)	(1.40)	
IN	0.550	-0.183	27.7
	(2.85)	(-1.13)	
NV	0.539	0.233	31.7
	(2.96)	(1.17)	
NM	0.371	0.085	14.1
	(2.12)	(0.58)	
TX	0.347	0.379	27.5
	(2.55)	(2.60)	

B Pre-Tail Distribution and Local Granularity

In this section, we show how differences between tail decay rates can affect local granularity. In what follows, we first describe an economy using the same notation used in Gabaix (2011). Subsequently, we describe the importance of tail decay rate for the granularity of the economy.

B.1 Model Setup

Assume we have an island economy with N firms. Also assume that we have an endowment economy, meaning that production is exogenous. We define a firm's sale growth as:

$$Sale\ growth = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} = \sigma_i \varepsilon_{i,t+1}. \tag{B1}$$

Also, if the good is homogeneous without any factor input, we can write the total GDP as:

$$GDP_t \equiv Y_t = \sum_{i=1}^{N} S_{i,t}. \tag{B2}$$

Subsequently, GDP growth and GDP volatility are defined as:

$$GDP\ growth = \frac{\Delta Y_{i,t+1}}{Y_{i,t}} = \sum_{i=1}^{N} \sigma_i \frac{S_{i,t}}{Y_t} \varepsilon_{i,t+1}, \tag{B3}$$

$$\sigma_{GDP} = (\sum_{i=1}^{N} \sigma i^2 (\frac{S_{i,t}}{Y_t})^2)^{1/2}. \tag{B4}$$

Considering $\sigma_i = \sigma$ for all firms, we can re-write Equation (B4) as:

$$\sigma_{GDP} = \sigma h, \tag{B5}$$

where h is the Herfindal of the economy:

$$h = (\sum_{i=1}^{N} (\frac{S_{i,t}}{Y_t})^2)^{1/2}. \tag{B6}$$

Assume that the firm size distribution is drawn from a distribution with infinite variance (i.e., size distribution is fat-tailed). Therefore, the power-law distribution for the firm size is:

$$Pr(S \geq x) = ax^{-\xi}. \tag{B7}$$

To complete the description of the economy, we calculate σ_{GDP}. For this analysis, we need to calculate h, for which we need to make an assumption about ξ. If $1 < \xi \leq 2$, as $N \to \infty$ the distribution will have infinite variance. Following Gabaix (2011), we can show that when $1 < \xi \leq 2$, $\sigma_{GDP} = \frac{v_\xi}{N^{1-1\ \xi}}\sigma$, and when $\xi = 1$, $\sigma_{GDP} = \frac{v_\xi}{LnN}\sigma$.

B.2 Tail Decay Rate and Granularity

Based on the above framework, we show that two fat-tailed distributions with the same tail exponent but different pre-tail exponents, can have different effects on σ_{GDP}.

To support this idea, consider two fat-tailed distributions, I and II, both with a tail exponent of $\xi_1 = c$, where c can be either between 1 and 2, or be equal to 1. Assume further that the location of both distributions' tails is at s^*, that is, for a positive amount of θ, $Pr(S \geq s^*) \gg Pr(S \geq s^* + \theta)$. Finally, assume that despite the similar overall tail exponents, distribution I has a smaller tail decay rate (i.e., it has a higher level of obesity before its tail). Specifically, consider a pre-tail Pareto exponents of a for distribution I, and b for distribution II, where $a > b > c$. This means that for $\vartheta > \theta > 0$, $Pr(S_{II} \geq s^* - \vartheta) \ll Pr(S_I \geq s^* + \vartheta)$, and $Pr(S_{II} \geq s^* - \vartheta) \gg Pr(S_I \geq s^* - \vartheta)$.

Based on the above argument, it is straight forward to show that the decay rate of extreme values in distribution I is $\frac{\sigma}{N^{1-\frac{1}{a}}}$, which is smaller than the tail decay rate of in distribution II ($\frac{\sigma}{N^{1-\frac{1}{b}}}$). This analysis suggests that because the effect of extreme values diffuses with a smaller rate in distribution I, this distribution is more likely to be empirically identified as a granular economy. Consistent with this finding, the U.S. states that have a fat-tailed distribution and a small tail decay rate are more likely to be empirically identified as granular economies.

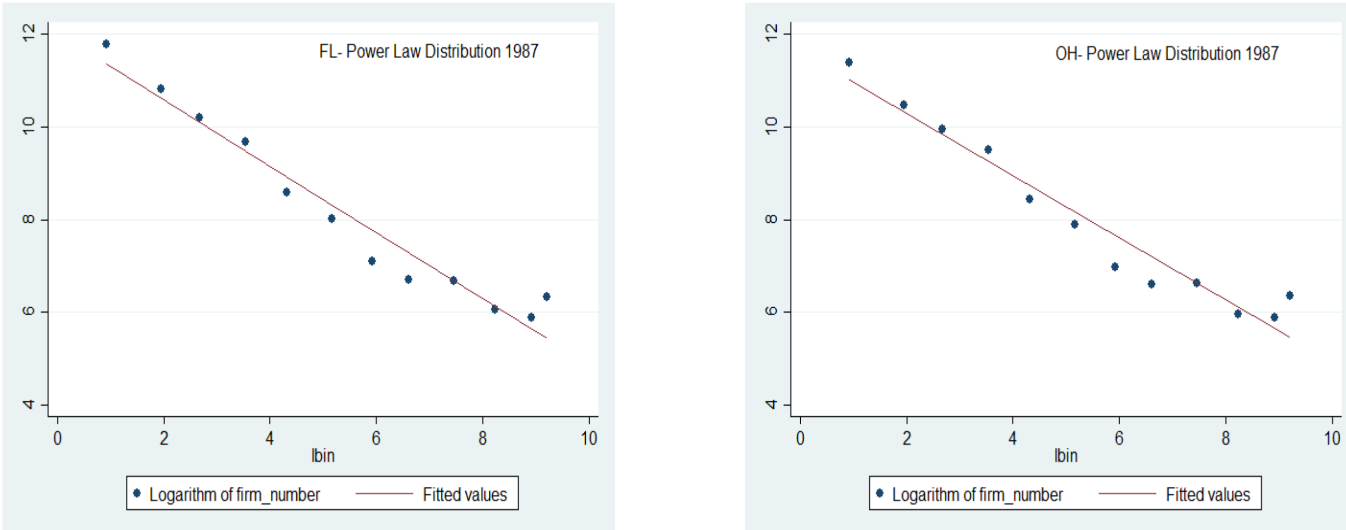

Figure B1: **Power-Law Distribution: Example**
This figure shows power-law distribution of firm size (by employees) in two random states: FL and OH in a random year (1987). Firm data are from the Small Business Administration (SBA).

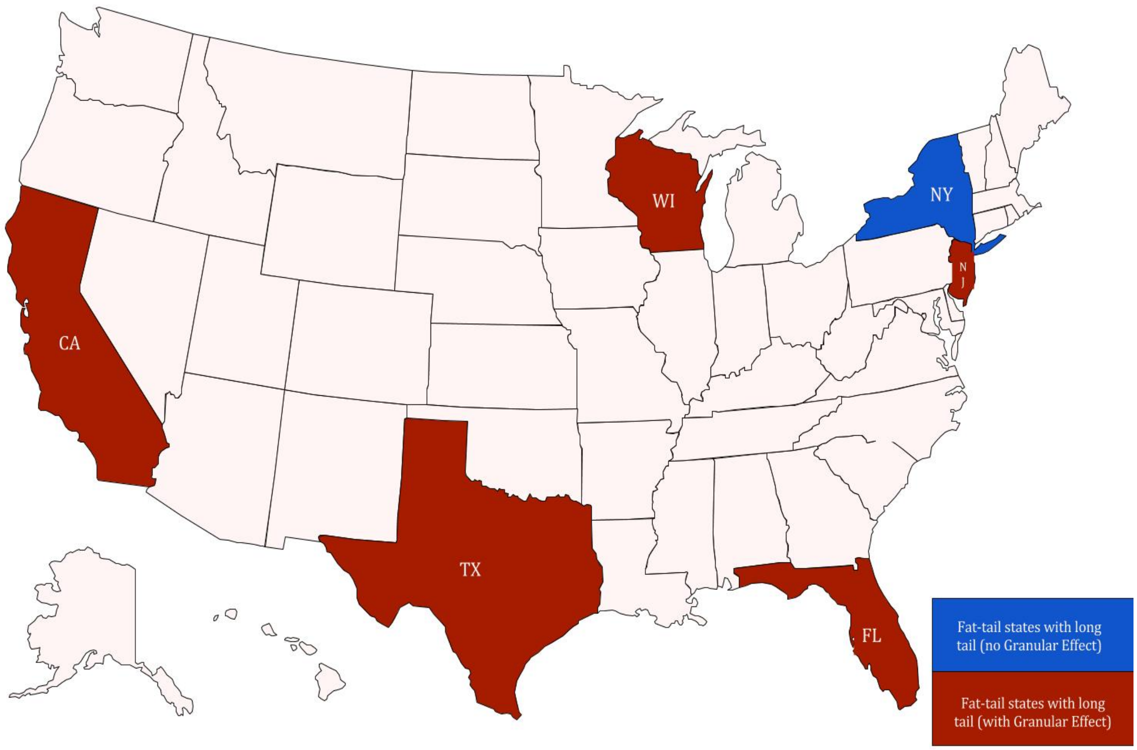

Figure B2: **States with Small Tail Decay Rate**
This figure shows states with a small tail decay rate (i.e., least pre-tail obesity). States with the granular effect are shown in red and those without the granular effect are shown in blue.

Table B1: **Number of Firm size in Various Size Classes**
This table shows the number of firms in various size classes (by the number of employees) in 1987 for two (random) states: FL and OH. The data are from the SBA.

(1) State	(2) Year	(3) Class	(4) Number of Firms
FL	1987	Total	236,751
FL	1987	1-4	131,351
FL	1987	5-9	49,856
FL	1987	10-19	27,119
FL	1987	20-49	15,858
FL	1987	50-99	5,359
FL	1987	100-249	3,060
FL	1987	250-499	1,196
FL	1987	500-999	809
FL	1987	1,000-2,499	802
FL	1987	2,500-4,999	424
FL	1987	5,000-9,999	358
FL	1987	10,000+	559
State	Year	Class	Number of Firms
OH	1987	Total	173,549
OH	1987	1-4	98,546
OH	1987	5-9	33,127
OH	1987	10-19	18,792
OH	1987	20-49	12,020
OH	1987	50-99	4,067
OH	1987	100-249	2,649
OH	1987	250-499	1,160
OH	1987	500-999	755
OH	1987	1,000-2,499	900
OH	1987	2,500-4,999	495
OH	1987	5,000-9,999	387
OH	1987	10,000+	651

Table B2: **Tail Decay Rate and Empirical Test of Granularity**
This table shows the relationship between tail decay rate of firm size distribution and the granularity of local economies. Tail decay rates show the pre-tail exponent of the firm size distribution for states that have a fat-tailed distribution. The R^2 is from Regression (5). We rank states based on the estimated R^2.

(1)	(2)	(3)
State	Tail Decay Rate (%)	R^2 (%)
CA	90.1	28.5
FL	92.2	21.3
WI	84.7	13.1
NJ	86.7	11.8
TX	86.7	8.7
NY	90.8	8.1
NC	85.5	8.1
OH	83.5	5.4
IL	82.0	5.1
PA	84.4	1.1
MN	83.0	0.2

Table B3: **Firm Network and Empirical Test of Granularity**

This table shows the relationship between firms' networks and the granularity of local economies. We proxy for firm networks using three variables: (1) average sensitivity of non-dominant firms' excess returns to the average excess returns of locally dominant firms in the same state (Equation (10)), (2) average sensitivity of non-dominant firms' operating income growth to the average operating income growth of locally dominant firms in the same state (Equation (11)), and (3) average sensitivity of non-dominant firms' cash flow growth to the average cash flow growth of locally dominant firms in the same state. Panel A shows the estimated betas along with the estimated R^2 from Regression (5) for the sample of states with non-fat firm size distribution. In Panel A, we rank states based on the estimated R^2. Unreported estimates for a state indicate missing information in that state (i.e., in WY). Panel B shows the Pearson correlation between average betas and R^2 from Panel A. Correlation numbers that are shown in bold text indicate statistical significance at the 5% level confidence.

Panel A: Average Estimate of Betas

(1) State	(2) Excess Return	(3) Operating Income	(4) Cash Flows	(5) R^2 (%)
VT	1.082	4.101	3.525	21.7
MS	1.313	0.083	-0.526	17.7
AL	0.802	0.064	-0.082	16.2
AZ	1.973	0.201	0.125	16.1
IN	1.070	0.654	0.736	12.8
OK	1.052	-0.098	0.161	12.2
NV	1.244	0.027	-0.574	10.9
NM	1.005	-0.118	1.259	9.8
ID	1.224	0.322	-0.275	7.0
MA	1.004	0.155	0.356	7.0
MD	0.671	0.661	-0.170	6.8
AR	0.582	0.246	0.540	6.1
MO	0.836	0.118	0.115	6.1
UT	0.664	-0.024	-0.392	6.0
ME	0.470	-0.316	1.351	5.8
IA	0.432	-0.314	0.634	5.5
LA	0.546	0.506	1.008	5.5
NE	0.825	0.562	0.586	5.3
NH	0.814	0.631	-2.313	5.0
OR	1.086	0.287	0.553	4.9
WV	1.920	-0.450	0.923	4.6
TN	1.084	-0.011	0.274	4.2
VA	0.767	0.137	0.241	4.2
MI	1.240	0.359	-0.260	3.8
RI	0.996	1.069	1.016	3.8
KS	1.215	-0.048	0.253	3.7
WY	2.121	–	–	3.4
CT	1.354	0.766	0.719	3.1
MT	0.725	0.761	-2.006	2.9
WA	0.851	-0.455	0.070	2.5
DE	1.139	-0.097	0.713	2.0
GA	0.765	0.517	0.336	1.8
KY	1.044	0.051	0.197	1.6
SC	1.204	0.067	-0.665	1.5
CO	0.701	0.544	-0.697	0.8
SD	0.917	-0.516	1.805	0.6
ND	1.113	0.001	-2.694	0.1

Table B3: **Firm Network and Empirical Test of Granularity (cont'd)**

Panel B: Pearson Correlation

(1)	(2)	(3)
Average Beta	Non-Fat States	Non-Fat and Granular States
Excess Return	0.1614	0.1436
Operating Income	**0.4358**	**0.7278**
Cash flows	**0.3125**	0.4694

C Which Firms Affect Non-Granular States?

In the previous sections, we identified granular states as those for which idiosyncratic shocks to locally dominant affect their economic growth. However, not all states are granular, which raises the concern that the role of local productivity shocks on the local/regional level might be limited. We conjecture that the lack of granularity for all states might be related to the fact that state borders do not always correspond to actual economic borders. Therefore, the economy of non-granular states might be affected by shocks to firms located out of the state borders.

We explore this conjecture by studying the impact of three groups of companies on the GDP growth of non-granular states. First, to set the stage, we focus on nationally large firms (i.e., top-100 U.S. firms). Then, we examine the role of regional locally dominant firms, and lastly, we examine the impact of out-of-region locally dominant firms. In the analysis of this section, we exclude the effects of locally dominant firms.

C.1 Nationally Large Firms

To test the economic effects of nationally large firms, each year we identify the top-100 firms in the U.S. based on prior year's net sales. Next, using the same method described in Section 2, we calculate the granular residual of nationally large companies (Γ_t). We then run a time-series regression similar to Regression (5), using Γ_t and Γ_{t-1} as the main independent variables.

Panel A of Table C1 reports states for which the estimated R^2 is above 8%. As shown in Column (1), the top-100 U.S. firms affect New York's economy more than any other state ($R^2 = 35.9\%$). Table C1 also shows that the granular residual of the largest U.S. firms (i.e., Γ_t) does not have a considerable economic impact across *all* states. For example, although shocks to locally dominant firms in Florida can explain 21.3% of the local fluctuations, shocks to top-100 U.S. firms do not explain a significant portion of the state's economic fluctuations. Ultimately, we find 11 states that are not significantly affected by shocks to nationally large firms, which includes Washington, Nebraska, Texas, Mississippi, Florida, South Carolina, Ohio, Michigan, New Jersey, Massachusetts, and Maine. We show the geographic distribution of these states in Figure C1.

C.2 Regional Locally Dominant Firms

Next, we identify states that are economically affected by shocks to locally dominant firms in the state's region or division. We define the region of a state as the group of states that share a border with that state. For example, California's region includes Arizona, Oregon, and Nevada. For a state's division, we use the 9 U.S. Census divisions: Pacific, Mountain, West North Central, East North Central, West South Central, East South Central, South Atlantic, Middle Atlantic, and New England.[1]

As in Section 3.1, we identify the states that are affected by the locally dominant firms in their region or division, using the R^2 from Equation (5). To identify the locally dominant firms for the division (or region), of a state, we exclude the effect of the top-100 U.S. firms and the state's own locally dominant firms. Panels B and C of Table C1 report states in which shocks to locally dominant firms at the division and regional levels explain more than 8% of the states' GDP growth. For instance, the estimation results in Column (3) show that Washington is mostly affected by the granular residual of locally dominant firms located in the Pacific division (the explanatory power of these companies is 29% ($R^2 = 28.9\%$)). Moreover, we find that Arkansas ($R^2 = 24.8\%$), and Pennsylvania ($R^2 = 20\%$)

[1] Based on the region and division categorizations, there is a possibility of overlap between the set of locally dominant firms for a specific state's regional area and division. For example, locally dominant firms headquartered in Oregon are considered both in California's region and division analysis because Oregon is both in California's division (Pacific) and also shares a border with California.

are among the states that are mostly affected by the locally dominant firms that are headquartered in the states' regions. We show the geographic distribution of these states in Figures C2 and C3.

C.3 Out-of-Region Locally Dominant Firms

Finally, for completeness, we study the economic impact of out-of-region firms on the business cycle of U.S. states. Specifically, for each state, we examine the economic power of locally dominant firms that are headquartered outside of the state's region (or division). In particular, for each state, we identify a set of dominant firms that, after excluding the top-100 U.S. firms, the state's locally dominant firms and the state's division and regional dominant firms, are among the top quartile of firm size distribution, where size is the prior year's net firm sales. In Panel D of Table C1 we report states that are affected by these companies. In Figure C4, we depict the geographic distribution of these states.

C.4 Which Firms Affect each State?

Collectively, all our results in Appendix C suggests that firm-level shocks are important for state-level economic conditions. Some states (i.e., the granular states) are affected by the locally dominant firms headquartered in these states. Other states are affected by non-local firms. To summarize all these findings, we present which U.S. states are affected by various groups of firms in Figures C1 to C4. The overlap of these figures provides a reference for the set of firms that have systematic information for the economic growth of each state.

We further summarize the information in Figures C1 to C4 in Figure C5. In this figure, we plot the relative economic importance of different groups of firms on the GDP growth of each state. For example, for Florida, the most economically significant firms are locally dominant firms that are headquartered in Florida. On the other hand, the most influential firms for New York are the top-100 U.S. firms. Overall, the totality of our findings provides a complete picture of the origins of economic fluctuations at the state level.

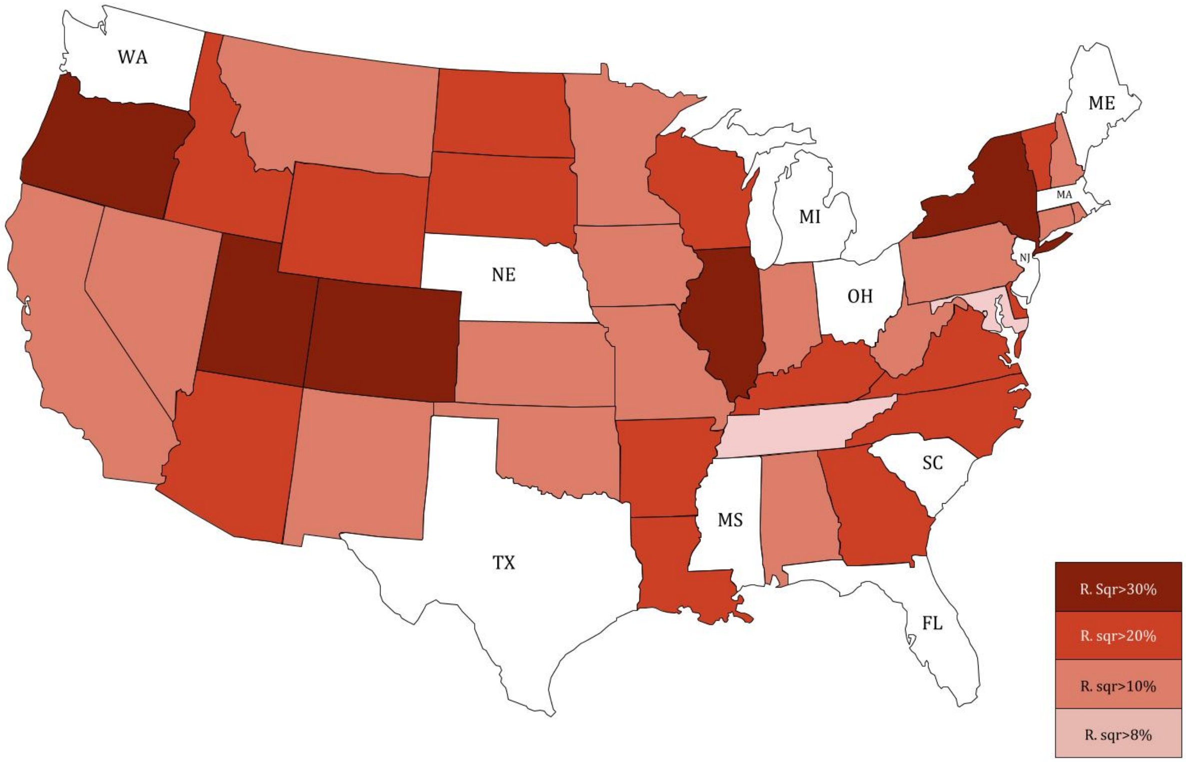

Figure C1: **States Affected by the Top-100 U.S. Firms**
This figure shows the geographic distribution of states in which idiosyncratic shocks to the top-100 U.S. firms explain more than 8% of the state's economic fluctuations. States in which nationally large firms have a larger economic impact are shown in a darker shade. This figure also identifies 11 states (shown with their name) in which shocks to the top-100 firms do not explain the local business cycles. A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per capita is from the BEA. The sample period is from 1977 to 2017.

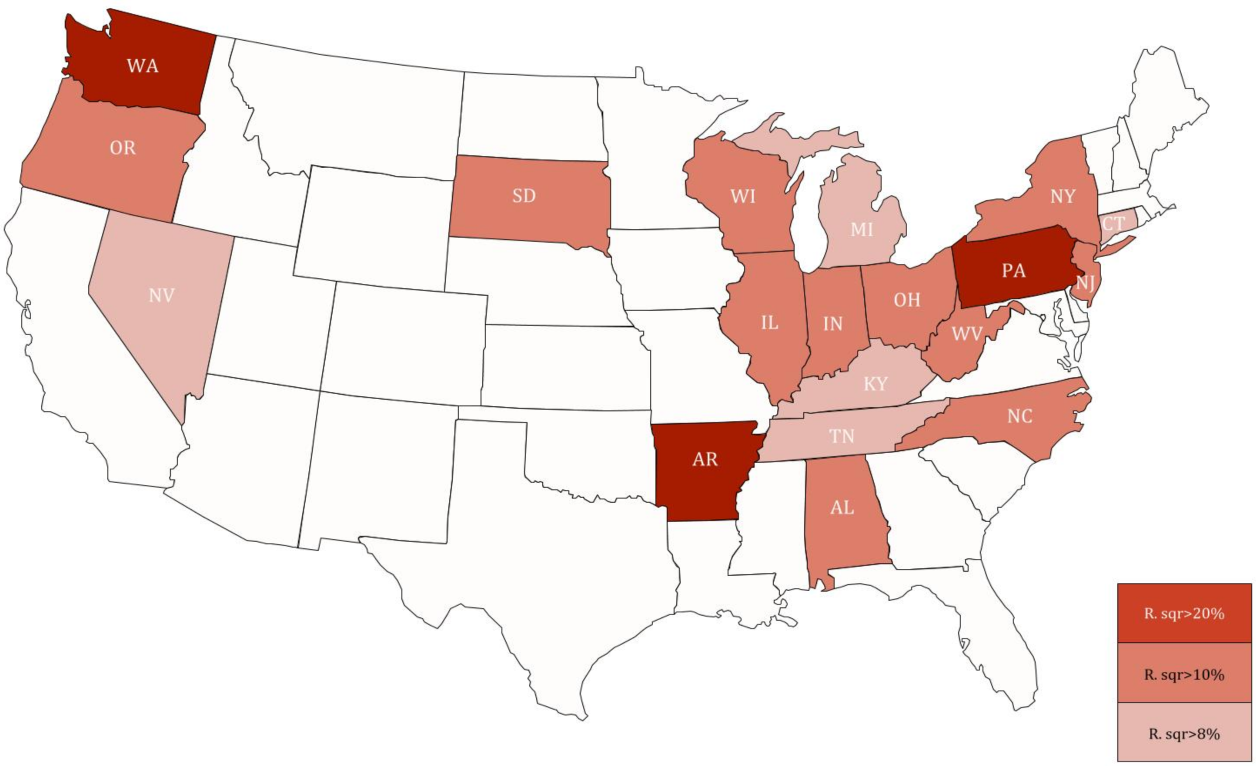

Figure C2: **States Affected by the Locally dominant Firms in the State's Division**
This figure shows states in which shocks to the locally dominant firms in states' divisions explain more than 8% of the states' GDP growth. Division areas are defined based on the U.S. Census categories. Locally dominant firms at each division are defined as firms that, after excluding the top-100 U.S. firms and states' locally dominant firms, are among the top quartile of the division's size distribution, where size is the prior year's net firm sales. A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per capita is from the BEA. The sample period is from 1977 to 2017.

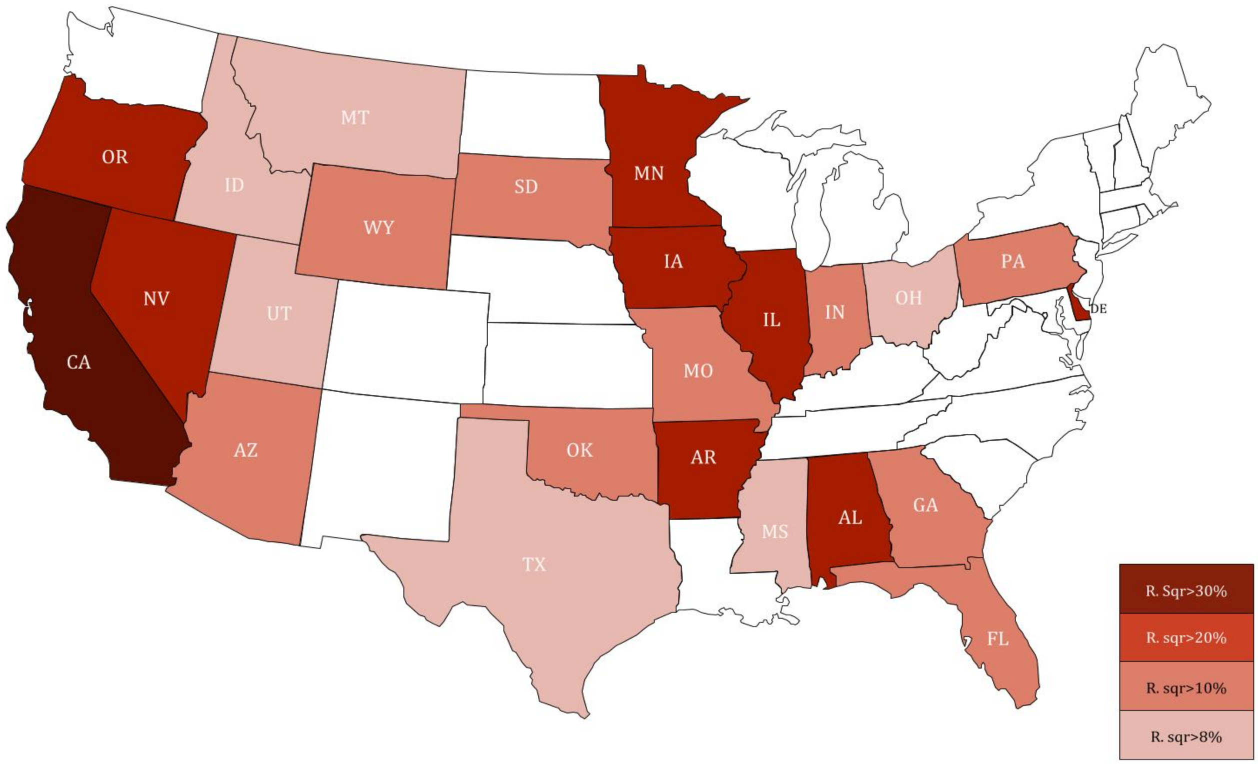

Figure C3: **States Affected by the Regional Locally Dominant Firms**
This figure shows states in which shocks to the locally dominant firms in states' regional areas explain more than 8% of the states' GDP growth. A state's regional area is defined as a group of states that share a border with the state. Locally dominant firms at each regional area are defined as firms that, after excluding the top-100 U.S. firms and states' locally dominant firms, are among the top quartile of the region's size distribution, where size is the prior year's net firm sales. A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per capita is from the BEA. The sample period is from 1977 to 2017.

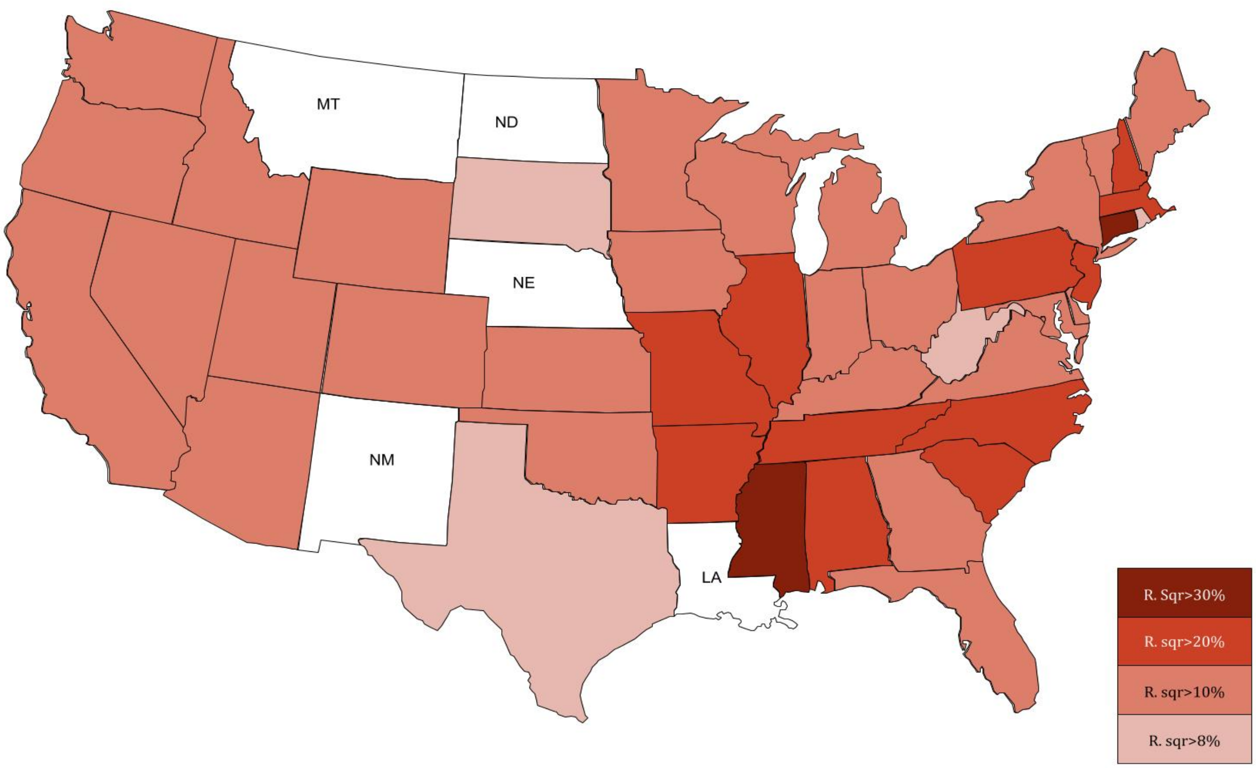

Figure C4: **States Affected by the Locally dominant Firms across the U.S.**
This figure shows states that the idiosyncratic shocks to the locally dominant firms across the U.S. can explain more than 8% of the states' GDP growth. Locally dominant firms across the U.S. (for a state) are defined as firms that, after excluding the top-100 U.S. firms, the state's locally dominant firms, and the state's regional and division locally dominant firms, are among the top quartile of firm size distribution, where size is the prior year's net firm sales. This figure also identifies 5 states (shown with their name), in which shocks to locally dominant firms across the U.S. do not explain a significant portion of the local business cycles. A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per capita information is from the BEA. The sample period is from 1977 to 2017.

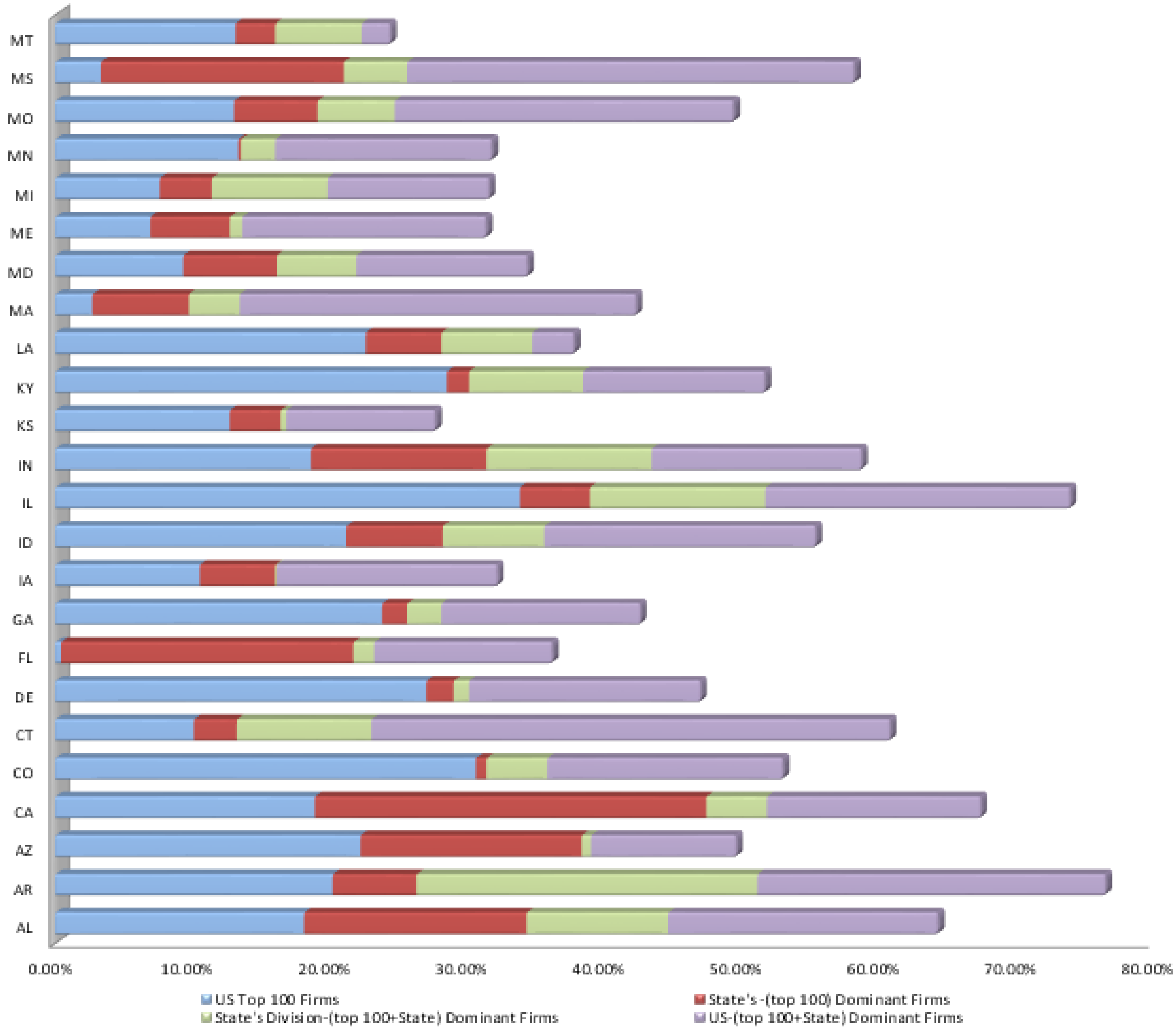

Figure C5: **Economically Important Firms per State**

For each U.S. state, this figure shows the economic effects of (1) the U.S. top-100 firms, (2) locally dominant firms headquartered in the state, (3) locally dominant firms in the state's division area, and (4) locally dominant firms across the U.S. on the state's GDP growth. The U.S. top-100 firms are the 100 largest firms in the U.S. Locally dominant firms in each state are defined as firms that, after excluding the top-100 U.S. firms, are among the top quartile of the state's firm size distribution. Locally dominant firms at each division are defined as firms that, after excluding the top-100 U.S. firms and the state's locally dominant firms, are among the top quartile of the division's firm size distribution. Locally dominant firms across the U.S. are defined as firms that, after excluding the U.S. top-100 firms, locally dominant firms at the state and division levels, are among the top quartile of firm size distribution. In all specifications, size is the net sales of firms in the prior year. In the figure, the Y axis shows states' name and the X axis shows the estimated R^2 (see Section C). A state's GDP growth is the log change of the state's real GDP per capita. Firm data are from Compustat. Real GDP per-capita is from the BEA. The sample period is from 1977 to 2017.

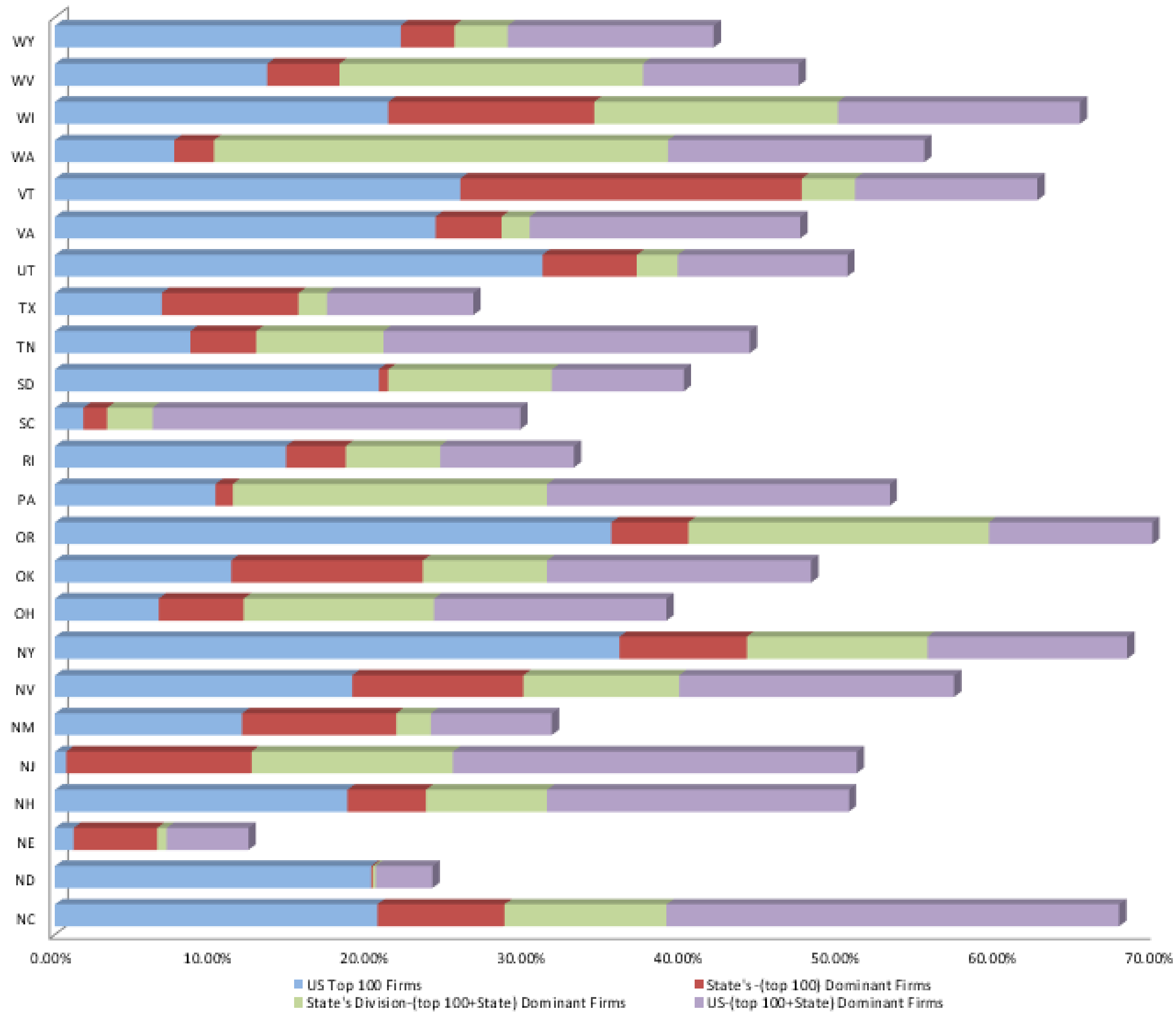

Figure C5: **Economically Important Firms per State – Continued**

Table C1: **What Group of Firms Affect Each U.S. State**

This table shows a set of economically significant firms per state that can significantly affect the state's economic growth. Column (1) shows states that are affected by productivity shocks to the top-100 U.S. firms. Columns (3) and (5) show states that shocks to locally dominant firms in states' division and regional areas explain more than 8% of the local business cycles. Column (7) shows states that shocks to out-of-state locally dominant firms explain more than 8% of the states' GDP growth. The top-100 U.S. firms are the 100 largest firms in the U.S. Locally dominant firms at each division (or region) are defined as firms that, after excluding the top-100 U.S. firms and the state's dominant firms, are among the top quartile of firm size distribution. Locally dominant firms across the U.S. are defined as firms that, after excluding the top-100 U.S. firms, locally dominant firms at the state and division levels, are among the top quartile of firm size distribution. In all specifications, size is the net sales of the firm in the prior year. Firm data are from Compustat. Real GDP per capita is from the BEA. The sample period is from 1977 to 2017.

Panel A: Top-100 U.S. Firms		Panel B: Division Locally Dominant Firms		Panel C: Regional Locally Dominant Firms		Panel D: Out-of-State Locally Dominant Firms	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State	R^2 (%)	State	R^2 (%)	State	R^2 (%)	State	R^2 (%)
NY	35.90	CA	39.60	WA	28.90	CT	37.80
OR	35.40	NV	27.20	AR	24.80	MS	32.60
IL	33.80	AR	25.90	PA	20.00	MA	28.90
UT	31.00	AL	24.40	WV	19.30	NC	28.80
CO	30.60	DE	23.60	OR	19.10	NJ	25.70
KY	28.50	MN	23.00	WI	15.50	AR	25.40
DE	27.00	OR	21.40	IL	12.80	MO	24.70
VT	25.80	IL	20.80	NJ	12.80	SC	23.40
VA	24.20	IA	20	OH	12.10	TN	23.30
GA	23.80	FL	13.40	IN	12.00	IL	22.20
LA	22.60	OK	13.30	NY	11.50	PA	21.80
AZ	22.20	GA	12.10	SD	10.40	ID	19.80
WY	22.00	MO	12.00	AL	10.30	AL	19.70
ID	21.20	PA	11.90	NC	10.30	NH	19.20
WI	21.20	AZ	11.10	NV	9.90	ME	17.80
SD	20.60	IN	10.80	CT	9.80	NV	17.50
NC	20.50	SD	10.60	MI	8.40	CO	17.20
AR	20.20	WY	10.00	KY	8.30	VA	17.20
ND	20.10	MS	9.80	TN	8.10	DE	16.90
CA	18.90	UT	9.80			OK	16.80
NV	18.90	OH	9.70			WA	16.30
IN	18.60	MT	9.40			IA	16.10
NH	18.60	ID	8.70			MN	15.80
AL	18.10	TX	8.50			CA	15.60
RI	14.70					WI	15.40
WV	13.50					IN	15.30
MN	13.30					OH	14.80
MT	13.10					GA	14.50
MO	13.00					KY	13.30
KS	12.70					WY	13.10
NM	11.90					FL	13.00
OK	11.20					NY	12.70
IA	10.50					MD	12.50
PA	10.20					MI	11.80
CT	10.10					VT	11.60
HI	9.40					KS	10.90
MD	9.30					UT	10.80
TN	8.60					AZ	10.60
						OR	10.40
						WV	9.90
						TX	9.30
						RI	8.50
						SD	8.40