Geographic Spillover of Dominant Firms' Shocks

Sima Jannati

University of Missouri-Columbia

ABSTRACT

This paper shows that productivity shocks to the 100 largest U.S. firms (by revenue) contain systematic information. Specifically, shocks to the top-100 firms predict future shocks to geographically close firms. Intra-sector trade links are an important economic channel for spillover effects. However, these spillovers are not restricted to firms' trade links only. Knowledge externalities and state income tax payments are other economic channels through which shocks propagate. Market participants do not fully incorporate the information contained in shocks to the top-100 firms. Consequently, a trading strategy that exploits the slow diffusion of information generates an annual risk-adjusted return of 5.4%.

JEL classification: G02, G14, G24.

Keywords: Top-100 firms; productivity shocks; systematic information; geographic spillover; information diffusion.

Please address all correspondence to Sima Jannati, University of Missouri, Trulaske College of Business, email: `jannatis@missouri.edu`. This article is based on my Ph.D. dissertation submitted to the University of Miami. I am grateful for the help and guidance of Alok Kumar, George Korniotis, Indraneel Chakraborty, and Alexandra Niessen-Ruenzi. I also would like to thank Jawad Addoum, David Hirshleifer, Alireza Tahbaz-Salehi, Stefanos Delikouras, Ville Rantala, Gennaro Bernile, William Bazley, Sarah Khalaf, Robert Viglione (discussant), Matthias Pelster (discussant), Mehmet Dicle (discussant), and Hui-Ju Tsai (discussant) and seminar participants at the Financial Management Association Annual meeting 2017, Southern Finance Association Annual meeting 2017, 8th Miami Behavioral Finance Conference, Ph.D. poster session at the American Finance Association Annual meeting 2018, Southwestern Finance Association Annual meeting 2018, Eastern Finance Association Annual meeting 2018, University of Miami, Georgia Institute of Technology, Virginia Commonwealth University, University of Missouri, California State University at Fullerton, and Cornerstone Research for helpful comments and suggestions. Any errors or omissions are my own.

1 Introduction

The U.S. economy comprises more than 5 million firms. Among these firms, a small number of companies are extremely large. The ten largest U.S. firms, for instance, represent one-fourth of the overall market capitalization (Malevergne et al. (2009)). These mega-cap firms substantially affect the national economy. Gabaix (2011) shows that productivity shocks to the 100 largest U.S. firms explain one-third of the U.S. business cycle. Despite the importance of the largest U.S. firms, their economic impact on other firms has not been thoroughly examined.

In this study, motivated by the evidence in Gabaix (2011), I examine whether firm-specific productivity shocks to the 100 largest U.S. firms (hereafter, dominant firms) contain relevant information for other firms. I also identify the economic channels through which shocks to the largest firms spillover to other firms. This analysis provides a microfoundation for Gabaix's (2011) results by identifying the mechanism through which shocks to the largest firms in the economy aggregate.

Firms can be connected in different ways. For example, they can have intra-sector trade linkages, or firms may choose to locate in close geographic proximity of each other. In this paper, I investigate the propagation of dominant firms' shocks through the geographic networks they form with other firms. Within these networks, I identify multiple economic channels that lead to spillover of productivity shocks.

My key conjecture is that productivity shocks to dominant firms spread geographically and affect future shocks to other firms. To test this hypothesis, I identify local non-dominant firms as those headquartered in the same state as the dominant firms. Further, I use two measures to proxy for firm-specific productivity shocks. First, consistent with Gabaix's (2011) methodology, I measure a firm's productivity shock as the difference between the company's productivity growth and the average growth of other comparable firms. This de-meaning procedure allows me to identify firm-specific shocks because I remove the effects of economy-wide shocks. In the second measure, I account for firms' heterogeneous response to economy-wide shocks and measure a firm's productivity shocks as the residual of the firm's productivity growth, over and above the firm's exposure to the average productivity growth of the economy, the average productivity growth of its sector, and geographical area.

The results indicate that shocks to dominant firms spillover geographically, as their productivity shocks are positively correlated with future shocks to other local firms. In economic terms, a 1-standard-deviation increase in the magnitude of dominant firms' shocks causes a 49-bps increase in the standard deviation of shocks to local non-dominant firms in the following year. Considering the average productivity growth of non-dominant firms (i.e., 4.4%

per year); this effect is economically significant. Subsequently, these spillovers translate into higher sales, higher cash flows, and higher earnings among local non-dominant firms.

Next, I examine the economic channels that can drive geographic shocks spillover. Motivated by prior studies (e.g., Cohen and Frazzini (2008); Foerster et al. (2011); Acemoglu et al. (2012); Kelly et al. (2013)), I first study the role of intra-sector trade links. Through these connections, I expect a higher level of geographic spillover effects on non-dominant firms that operate in the same industry as dominant firms. The results confirm the role of intra-sector connections. More precisely, restricting the sample to dominant and non-dominant firms that operate in the same industry increases spillover effects in a geographical area from 49 bps (in the baseline analysis) to 2 percentage points.

The intra-sector linkage is an important economic channel for shock propagations, but it may not be the only channel. Dominant firms considerably affect their local economies. For example, productivity shocks to General Electric and United Technologies, the only two dominant firms in Connecticut, explain more than 17% of the state's gross domestic product (GDP) growth. This local impact can occur, for instance, via dominant firms' knowledge externalities, state income tax payments, new job opportunities, or through dominant firms' impact on local entrepreneurial activities. Therefore, a higher level of productivity shocks to dominant firms can lead to higher economic growth within their geographic areas, which, in turn, can induce a higher level of growth opportunities for other local firms. Clearly, this effect can occur beyond intra-sector connections between dominant firms and other neighboring firms.

To show that intra-sector links do not exclusively drive geographic spillovers of dominant firms' shocks, I perform three tests. First, I restrict the sample to local non-dominant firms that do not operate in the same industry as the dominant firms. I find that the geographic spillover effects remain both statistically and economically significant. This result remains consistent when I use different classification of firms' industries. Second, I use Hoberg and Phillips's (2016) text-based network industry classification (TNIC) data and additionally exclude dominant and non-dominant firm pairs that have overlapping business operations. That is, I remove dominant and non-dominant pairs that share the same sector or marketplace from the sample. The effects are similar even when I exclude these firms. Lastly, in addition to firms' intra-sector and product market linkages, I remove direct and indirect customer-supplier links. To do so, I use Input/Output (IO) data available on the Bureau of Economic Analysis (BEA) and exclude dominant and non-dominant firms that have trade links between their sectors (Menzly and Ozbas (2010)). Moreover, I follow Cohen and Frazzini (2008) to identify and exclude firms with direct customer-supplier links. Again, I find consistent results.

These results suggest that indirect connections between the largest firms in the economy and other firms can be economically meaningful. To identify the exact channels through which the geographic spillover of shocks occurs, I focus on several alternative mechanisms. The shock propagation mechanisms are likely to be context specific and vary from one local area (or dominant firm) to another. Despite this potential heterogeneity, I focus on the role of *knowledge externalities* and *state income tax payments* as key mechanisms of the geographic spillovers, beyond trade linkages. I focus on these two channels because they are applicable to most of dominant firms.

Dominant firms represent a considerable proportion of the patents issued in their local areas. For instance, Microsoft accounts for more than 80% of the patents annually issued in Washington. The knowledge externalities of dominant firms benefit the economic growth of firms' local areas (Carlino (1995)). Moreover, firms that are geographically closer to dominant firms can learn and use dominant firms' innovations and, subsequently, experience larger productivity growth (Jaffe et al. (1993); Kogan et al. (2017)). Through the knowledge externalities channel, I expect a stronger spillover effect when dominant firms account for a larger proportion of the patents issued in their local areas. Moreover, the geographic spillover of shocks should be stronger between dominant and non-dominant firms with similar innovations or when patents of a dominant firm are mostly cited by a local non-dominant firm (i.e., when patents of dominant firms are highly, locally relevant).

The results provide supporting evidence of the role of knowledge externalities in propagating productivity shocks. All else equal, geographic spillovers are stronger when a dominant firm accounts for a higher proportion of patents issued in its headquarter state. Similar results hold when I account for the value of patents, using patents' forward citations (Kogan et al. (2017)). Geographic spillovers increase to over 10 percentage points between pairs of dominant and local non-dominant firms that, despite not sharing the same sector, have patents in similar subclasses. Further, geographic spillovers raises to 4 percentage points when patents of dominant firms are mostly cited by local non-dominant firms.

An additional mechanism through which dominant firms make a local impact is their state income tax payments. Every year, on average, a dominant firm pays over $42 million in income taxes to its local government. Subsequently, local governments use this financial source to develop state infrastructure. Development of the state infrastructure can positively affect the growth opportunities available to local non-dominant firms (Firebaugh and Beck (1994); Levine (1997)). The results indicate that a 1-standard-deviation increase in the total income taxes of a state increases the next year productivity growth of its local firms for 4 percentage points. This increase is over and above unobserved characteristics over time or within the state, that may affect the productivity of local businesses. Given the importance of state-level tax budgets on the productivity of local firms, I expect geographic spillovers to be stronger in states in which dominant firms account for a larger proportion of the state's total income taxes. The results suggest that the tax channel is important. All else equal, the spillover effect increases to 1.3 percentage points in states in which dominant firms pay a larger proportion of the state's total income taxes.

Overall, the results indicate that shocks to the largest firms in the economy cause spillover effects that reach other firms in a geographical area. Spillovers can occur through direct connections (such as intra-sector trade linkages) or indirect interactions (such as knowledge externalities or tax payments) between firms. For robustness, I show that geographic spillovers are not driven by the effects of common local (or industry) shocks. Moreover, I show that accounting for the level of economic activity in firms' headquarter states results in a stronger spillover of shocks. The results also stay robust when I use an alternative measure of geographic proximity, such as metropolitan statistical areas (MSAs) or when I use total factor productivity (TFP) to measure firms' productivity. I show that the results are not primarily driven by states with the highest agglomeration of dominant firms. Finally, the results remain consistent when I account for the impact of merge activities or the recent financial crisis on firms' productivity growth.

In the next step, I examine the implications of the above findings on asset prices. Given that productivity shocks to dominant firms contain information about the future fundamentals of local non-dominant firms, they should be priced in the market. I conduct two tests to analyze whether equity prices incorporate this information. First, I develop a geography-based trading strategy. Specifically, I form a zero-cost portfolio that goes long (short) on non-dominant firms in states in which productivity shocks to dominant firms are the largest (smallest). This portfolio generates a monthly alpha of 44 bps, which translates into an annual risk-adjusted excess performance of 5.4%. This performance is robust to the choice of a risk-adjustment model. Further, the results suggest that this positive alpha is primarily driven by the market's inattention to connections between dominant and local non-dominant firms, beyond trade linkages: the risk-adjusted performance of the long-short portfolio increases to over 70 bps per month, when I restrict the sample to dominant and local non-dominant firms that operate in different sectors.

For the second test, I perform a double-sorted analysis. In addition to sorting the U.S. states on the average productivity shocks of dominant firms, I independently sort non-dominant firms on the exposure of their monthly returns (i.e., beta) to dominant firms' returns. If the positive alphas are primarily driven by the information contained in dominant firms' shocks, I expect non-dominant firms with higher betas to outperform firms with lower betas. The results of the double-sorted analysis confirm this conjecture: the long-short portfolios of the high-beta non-dominant firms significantly outperform the portfolios of the low-beta firms by more than 60 bps per month.

In the last part of the paper, I test whether sell-side equity analysts, a group of sophisticated market participants, are aware of the impact that dominant firms have on local non-dominant firms. Specifically, I examine whether analysts' earnings forecasts respond to dominant firms' shocks, when they issue forecasts for non-dominant firms. Surprisingly, I do not find that analyst forecasts respond to shocks to dominant firms. This result suggests that even sophisticated market participants do not fully incorporate the information contained in shocks to the largest U.S. firms, that may affect neighboring firms beyond trade links.

The results in this paper contribute to several strands of the finance literature. First, a rapidly growing literature examines the propagation of firm-specific shocks (Foerster et al. (2011); Kelly et al. (2013); Acemoglu et al. (2016); Baqaee and Farhi (2017); Jannati et al. (2018)). In particular, Gabaix (2011) shows that productivity shocks to the 100 largest firms in the United States explain 30% of U.S. GDP growth. Compared to the impact of other macro-wide shocks (such as monetary shocks), the aggregate impact of these mega-cap firms is significant (Cochrane (1994)). In this study, I extend the macro-level evidence of Gabaix (2011) to a firm-level analysis and identify the economic channels through which shocks to the largest firms in the economy spillover to other firms.

The results also complement recent studies that provide evidence of indirect economic interactions between firms. Specifically, Dougal et al. (2015) document shock propagation over and above firms' intra-sector interactions. Parsons et al. (2016) show a positive lead-lag stock return relation between geographically close firms that operate in different sectors. These studies, however, are silent on the exact *economic channels* that cause these out-of-sector shock spillovers. Focusing on the impact of the largest firms in the economy, I provide evidence of the role of knowledge externalities and state income taxes in propagating productivity shocks, beyond firms' trade links.

Finally, I extend the literature on investor inattention (Hong and Stein (1999); Hirshleifer and Teoh (2003); DellaVigna and Pollet (2009); Menzly and Ozbas (2010); Hirshleifer et al. (2011)). For example, Cohen and Frazzini (2008) argue that investors do not pay attention to direct connections between companies. Expanding these findings, I show that different groups of market participants, including equity analysts, display limited attention to the information contained in large firms' productivity shocks that affect geographically close firms, even in the absence of intra-sector connections.

2 Data and Methods

In this section, I describe the data sets used in the empirical analyses. Next, I explain the main variables and illustrate the method I use to measure firm-specific productivity shocks.

2.1 Data Sources

To obtain information on firms' productivity and headquarter states, I use the Fundamentals Annual section of Compustat database. I use the Fama-French 48 industry portfolios to identify firm industries. I complement this classification with the TNIC data from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). Further I use data from Cohen and Frazzini (2008) and Kogan et al. (2017) to obtain information on firms' customer-supplier links and annual patents.

National- and state-level GDPs and information on industries' input and outputs are from the BEA. Following Biswas et al. (2017), I collect the real chained GDP in 2009 U.S. dollars from 1997 to 2015 and the real chained GDP in 1997 U.S. dollars before 1997. I use available changes in quantity indices to extend the out-of-state GDP series in 1997 U.S. dollars backward. I then convert the pre-1997 real chained GDP series from 1997 to 2009 chained U.S. dollars by using the ratio of 2009 U.S. dollars GDP to 1997 U.S. dollars in 1997, when both series are available.

Other firm information, such as daily prices, the number of shares outstanding, and monthly returns, is from the Center for Research on Security Prices (CRSP). I use the Institutional Brokers Estimates System (IBES) to obtain information on analysts' earnings forecasts. To identify analyst location and all-star position, I merge IBES with the data from Antoniou et al. (2016) and Huang et al. (2014). Finally, I use firms' 10-K and 8-K filings, which are available from the U.S. Security and Exchange Commission (SEC), to obtain information related to firm-specific events.

2.2 Variable Description

In what follows, I explain the dependent and explanatory variables used in the empirical analyses. I provide detailed information on the sources of each variable in Table A1.

2.2.1 Identification of Dominant Firms

I follow Gabaix (2011) to identify dominant firms. I sort firms based on their prior year's net sales and consider the top-100 largest firms as dominant firms. All other firms are classified as non-dominant firms.

I choose the above cutoff to be consistent with Gabaix's (2011) method. Given that this cutoff is arbitrary, I check the robustness of my results to this choice. Although the results are not tabulated, I find consistent outcomes when I extend (or shrink) the dominant firms' sample to the 150 (or 50) largest U.S. firms.

2.2.2 Productivity Shocks

I proxy for a firm's productivity using the ratio of its net sales per employee. Next, I measure firms' productivity growth as the annual log change in their productivity: Specifically,

$$Productivity\ Growth_{j,t} = ln(\frac{Sales_{j,t}}{Employees_{j,t}}) - ln(\frac{Sales_{j,t-1}}{Employees_{j,t-1}}). \tag{1}$$

To obtain the firm-specific component of productivity growth, I extract the effects of common shocks by de-meaning $Productivity\ Growth_{j,t}$ from the average productivity growth of other firms:[1]

$$Productivity\ Shocks_{j,t} = Productivity\ Growth_{j,t} - \frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,t}. \tag{2}$$

Next, following Gabaix's (2011) and Foerster et al.'s (2011) methodology I scale $Productivity\ Shocks_{j,t}$ using the ratio of the firm's net sales to total GDP. This scaling is motivated by Hulten's (1978) theorem, in which a firm that accounts for a bigger proportion of the GDP receives a higher weight in the analysis. Specifically,

$$Scaled\ Shocks_{j,t} = \frac{Sales_{j,t-1}}{GDP_{t-1}} \times Productivity\ Shocks_{j,t}. \tag{3}$$

In the baseline analysis I use Equation 3 to remain consistent with the methodology of Gabaix (2011). The above measure, however, ignores firms' heterogeneous exposure to economy-wide shocks. Therefore, I build a second measure of firm-specific productivity shocks, using the residual ($\varepsilon_{j,i,s,t}$) from the following pooled-panel regression:

$$\begin{aligned} Productivity\ Growth_{j,i,s,t} = \alpha_j + \beta_j^i\ Productivity\ Growth_{i,t} + \beta_j^s\ Productivity\ Growth_{s,t} + \\ \beta_j\ Productivity\ Growth_t + \varepsilon_{j,i,s,t}, \end{aligned} \tag{4}$$

where $Productivity\ Growth_{j,i,s,t}$ is the productivity growth of firm j in industry i, headquartered in state s at time t. $Productivity\ Growth_{i,t}$ shows the average productivity growth of firms in sector i. $Productivity\ Growth_{s,t}$ shows the average productivity growth of firms headquartered in state s, and $Productivity\ Growth_t$ is the average productivity growth of all firms in the sample at time t. The estimated residual captures firm-level idiosyncratic productivity shocks, over and above common industry-, geography-, or economy-wide shocks.

[1] To control for firm size, in Equation 2, I de-mean dominant (non-dominant) firms' productivity growth from the average productivity of all dominant (non-dominant) firms. However, I show the robustness of the results to other de-meaning processes.

In all specifications, I use an annual measure of firm shocks for two reasons. Data limitations at higher frequencies are the first reason. Specifically, Compustat does not provide quarterly information on firms' number of employees. In addition, as argued by Parsons et al. (2016), the geographic diffusion of information tends to be slower compared with likewise industry effects. Given that I aim to document shock propagation beyond intra-sector relations, annual data better allow for information diffusion within the region and, therefore, provides a more suitable framework.

To further explain the nature of the statistical measure, I provide examples in Table A2. In this table, for some of the dominant firms in the sample, I show a comparison between the estimated shocks and the nature of the events that these firms experienced. The explained examples cover positive and negative events that happened to dominant firms in different sectors, over different time periods. For example, using the explained measure (i.e., Equation 2), in 1999, I compute a productivity shock equal to -10.07% for "HCA Healthcare," a dominant firm headquartered in Tennessee. According to the company's 10-K and 8-K filings, the company was involved in a fraud case and had a growing number of uninsured and reimbursement pressures. Moreover, the measure yields a productivity shock equal to 8.4% for "Rockwell Automation," a dominant firm headquartered in Wisconsin. The company's filings indicate that the variable proxies for a considerable increase in the firm's revenues related to automation, semiconductor systems, and light vehicle systems. These examples, along with others in Table A2, provide further evidence of the accuracy of the statistical measure.

2.2.3 Firm-Level Explanatory Variables

To control for a firm's profitability and growth opportunities, I use the following variables: *Size*, *Leverage*, *Loss*, *Market-to-Book Ratio*, *Cash Flow*, and *Dividend Yield* (Addoum et al. (2017)). I also control for the lagged productivity shocks of the non-dominant firm to ensure that the shock propagation is beyond the effects of the firm's own shocks.

Size is the natural logarithm of total assets. *Leverage* is the sum of short-term and long-term debts, divided by total assets. *Loss* is a dummy variable that takes the value of 1 when operating income (dividend) is negative and 0 otherwise. *Market-to-Book Ratio* is the sum of market equity, short-term debt, and long-term debt, divided by the total assets. *Cash Flows* are the cash flows from operating activities, divided by total assets, and *Dividend Yield* is dividends, divided by shareholders' equities.

2.2.4 Analysts' Forecast Errors

To examine analysts' understanding of the effects that dominant firms have on non-dominant firms, I use the annual average of analysts' quarterly *Forecast Errors* and *Accuracy*. Following prior studies (e.g., Richardson et al. (1999); Hong and Kubik (2003); Kumar (2010)) I define analysts' forecast errors as

$$Forecast\ Errors_{i,j,q} = \frac{Value_{i,j,q} - Actual_{j,q}}{Price_j}, \tag{5}$$

where $Value_{i,j,q}$ is the predicted earnings issued by $analyst_i$ who covers $firm_j$ in $quarter_q$. $Price_j$ is the price of $firm_j$, 2 days before the analyst's forecast date, where the forecast date is the most recent forecast of the analyst (Bondt and Thaler (1990); Lim (2001); Hong and Kubik (2003)). Positive forecast errors, therefore, identify cases in which the analyst carries an optimistic opinion about the firm, and negative forecast errors indicate that the analyst is pessimistic about the company's performance. In the analysis, I use the annual average of quarterly forecasts, as opposed to annual forecast errors, because prior studies (e.g., Matsumoto (2002)) note that analysts' annual earnings forecasts have a higher level of bias. The results, however, are not sensitive to this choice.

Next, I define analyst accuracy as the absolute value of the forecast errors (Hong and Kubik (2003)). Specifically,

$$Accuracy_{i,j,q} = |\frac{Value_{i,j,q} - Actual_{j,q}}{Price_j}|. \tag{6}$$

Based on the above definition, a smaller value of accuracy identifies more accurate forecasts.

When studying analyst behavior, I include attributes that can affect their earnings forecasts. Specifically, I control for analysts' *Experience*, *All-star* position, *Location*, *Brokerage Size*, *Forecast Age*, and *Excess Information*. *Experience* is a dummy variable equal to 1 if an analyst, at a specific point in time, appears in the sample for more than 3 years (Hong and Kubik (2003)). To proxy for an analyst's geographic proximity, I define a dummy variable, *Local-analyst*, equal to 1 if an analyst's brokerage is located in the same state as the firm she covers (Malloy (2005)). *All-star* is a dummy variable equal to 1 if the analyst is ranked among the II All-Americans in the previous year (Kumar (2010)). *Brokerage Size* is equal to $log(1 + analysts\ number)$, where the analyst number shows the total number of analysts that work in the brokerage (Huang et al. (2014)). *Forecast Age* shows the number of days between the analyst's earnings forecast date and the actual announcement of the firm (Agrawal et al. (2006)). Finally, to control for the analyst's excess information about a dominant firm, I include a dummy variable, *Both-cover*, equal to 1 if, in addition to a local non-dominant firm, the analyst also had covered the dominant firm in the prior year.

2.3 Sample Formation and Estimation Strategy

I take several steps to build the final sample. First, I exclude firms not located in the United States. I also filter out oil and oil-related companies (SIC codes 2911, 5172, 1311, 4922, 4923, 4924, and 1389) and energy firms (SIC codes between 4900 and 4940). I do so because fluctuations in these firms' sales are mostly affected by worldwide commodity prices rather than by productivity shocks. I also exclude financial firms (SIC codes between 6000 and 6999) because financial firms' sales do not coincide with the underlying economic meaning of the measure used in this paper. I require that firms have sales and employee data available for the current and previous years. To form the analysts' sample, I exclude analysts with no or an unknown identification code. Further, to ensure that results are not driven by outliers, I winsorize all the continuous variables at the -/+ 1% level (Jegadeesh et al. (2004); Gabaix (2011); Hugon and Lin (2013)). The final sample contains a total of 225 dominant and 7,113 non-dominant firms between 1995 to 2015.[2]

As explained, I build a pooled-panel database to estimate the effects of dominant firms' shocks on local non-dominant firms. Specifically, for every dominant firm, I identify all non-dominant firms headquartered in the same state. I use the pooled panel, which allows me to correctly study the effects of a dominant firm on out-of-sector non-dominant firms.[3] However, constructing the panel in this way may raise the concern of a within-unit error correlation related to the panel's repeated values (i.e., dominant firms' shocks). To address this issue, I use Fama and Macbeth (1973) two-step regression method and adjust the standard errors using the Newey and West's (1987) method with a 6-year lag (Ortiz-Molina and Phillips (2014)).[4] Additionally, to ensure that the results are not sensitive to the repeated values in the pooled panel, I replicate the results for the Fama and Macbeth (1973) regression, where I use the weighted average of dominant firms' shocks as the main independent variable.

[2] In the analysis, I set 1995 as the sample starting point for two main reasons. First, some of the variables (such as TNIC and state citation shares data) are only available for more recent time periods. Second, many studies (e.g., Cohen et al. (2010)) suggest collecting analysts' information after 1992. Given that I need 3 years of data to proxy for analysts' *Experience* (Hong and Kubik (2003)), I use 1995 as the starting point of the sample, to have a consistent sample throughout the analyses. However, I show that the results are not sensitive to this choice. Specifically, the results stay consistent when I extend the sample back to 1963.

[3] Assume that in state X, there are two dominant firms, A and B, and a non-dominant company C. Assume further that firms A and C operate in the same industry. When studying the impact of dominant firms on out-of-sector local non-dominant firms, I exclude the effects that A might have on C, but I still consider the possible effects of B on C. A pooled-panel setup allows me to examine this impact.

[4] The estimation results remain identical when I choose a lag equal to 5 (or 4) years, like in Parsons et al. (2016) and in the method of Bali et al. (2016). However, I choose a lag of 6 years following Watson's (2008) suggestion (see the 2008 NBER summer lectures). Further investigation of the data also supports the persistence of dominant firms' shocks. For example, the effects of negative shocks to Textron in 2002 (see Table A2) appear more than 5 years later in the company's 10-K filing.

2.4 Summary Statistics

Figure 1 shows the geographic distribution of the dominant firms. For each state, I show firms—that at some point in the sample—are identified as a dominant firm. Figure 1 shows large firms, such as Coca-Cola, Microsoft, Intel, and Alphabet, among others. The geographic distribution indicates that New York, California, Illinois, and Texas have the highest agglomeration of dominant firms. Table B1 further shows the total number of dominant firms in each state. As shown in Column 3 of Table B1, dominant firms, on average, account for less than 5% of (public) firms in each state. Despite this low representation, these mega-cap firms have significant influence on the economic growth of their headquarter states. For instance, the only two dominant firms in Maryland (i.e., Lockheed Martin and Marriott International) explain over 30% of the state's GDP growth.

I report the summary statistics of the main variables for dominant and non-dominant firms in Panels A and B of Table 1. These statistics are comparable to those of prior studies (e.g., Frank and Goyal (2009); Addoum et al. (2017)). As shown, non-dominant firms have a higher level of volatility in productivity shocks (44% vs. 12% for dominant firms). This pattern holds true for firms' cash flows and leverage measures.

Also, dominant firms' net sales and number of employees are well above those of non-dominant firms. On average, dominant firms have net sales of $19.3 billion, but this number is $871 million for non-dominant firms. This difference is also salient in companies' state income tax payments. On average, every year, dominant firms pay $43 million in state income taxes, whereas non-dominant firms pay less than $3 million. Finally, Panel C of Table 1 reports the Pearson correlation between the main variables of interest. As shown, lagged productivity shocks of dominant firms positively correlate with shocks of non-dominant firms. This correlation is significant at the 5% level. Moreover, the correlation between dominant and non-dominant firms' contemporaneous shocks is statistically insignificant at the 5% level. This evidence further suggests that the proxy used to measure firm-specific productivity shocks (i.e., Equation 2) does not merely capture common market-wide shocks.

3 Geographic Spillover of Dominant Firms' Shocks

This section presents the main empirical findings. I first show the propagation of shocks from dominant firms to local non-dominant firms. Next, I identify multiple economic channels that lead to these spillovers. I end this section by providing various robustness tests.

3.1 Baseline Results

To begin, I examine whether productivity shocks to dominant firms spillover to geographically close firms. To this end, I run the following predictive Fama and Macbeth (1973) regression:

$$\textit{Non-Dominant Firm's Shocks}_{j,t+1} = \alpha_j + \beta_1\, \textit{Dominant Firm's Shocks}_{i,t} + \beta_2\, X_{j,t} + \varepsilon_{j,t+1}. \quad (7)$$

β_1, the coefficient of interest, shows the predictive power of a dominant firm's shocks on future shocks to a non-dominant firm that is headquartered in the same state. In all specifications, I control for a vector of variables ($X_{j,t}$) that can affect the non-dominant firms' productivity. Specifically, I control for firms' lagged productivity shocks, cash flows, leverage, dividend yield, market-to-book ratio, loss, and size.[5]

Column 1 of Table 2 shows that above the effect of a non-dominant firm's profitability, shocks to a dominant firm significantly predict productivity shocks to the local non-dominant firm. In economic terms, a 1-standard-deviation increase in a dominant firm's productivity shocks causes a 49-bps increase in the next period's shocks to a local non-dominant firm (coefficient = 0.0049; t-statistic = 2.46). Considering the average productivity growth of a non-dominant firm (i.e., 4.4% per year), this effect is economically significant.

Consistent with Gabaix's (2011) methodology, in the above model I use Equation 3 to measure firms' productivity shocks. This measure, however, assumes that economy-wide shocks have homogeneous effects on firms. To ensure that the results are not sensitive to this assumption, I repeat the analysis, using the estimated residual from Regression 4 (i.e., $\varepsilon_{j,i,s,t}$) as the proxy for firm-specific productivity shocks. As shown in Column 4 of Table 2, the estimates are economically and statistically stronger when I use the latter measure of shocks (coefficient = 0.0058; t-statistic = 4.67).

Next, I investigate the economic significance of geographic shock spillovers from dominant firms to local non-dominant firms. Specifically, I study the effects of a dominant firm's productivity shocks on local non-dominant firms' fundamentals, through the influence of the large firm on the non-dominant firm's productivity (i.e., $\textit{Dominant Firm's Shocks}_{i,t-1}$ to $\textit{Non-Dominant Firm's Shocks}_{j,t}$, and then $\textit{Non-Dominant Firm's Shocks}_{j,t}$ to $\textit{Non-Dominant Firm's Fundamentals}_{j,t}$).

Column 1 of Table A3 shows the effect of a non-dominant firm's productivity shocks on its earnings. A 1-standard-deviation increase in firm-specific shocks corresponds to a 1.5-percentage-point increase in contemporaneous earnings (coefficient = 0.0152; t-statistic = 5.08). Like with the earnings, firm-specific shocks positively and significantly affect the

[5]The results stay consistent, when I additionally control for the dominant firm's contemporaneous productivity shocks (i.e., $\textit{Dominant Firm's Shocks}_{i,t+1}$).

firm's net sales. Column 2 of Table A3 shows that a 1-standard-deviation increase in firm-specific shocks increases the firm's contemporaneous sales more than 3.7 percentage points (coefficient = 0.0368; t-statistic = 2.19). Finally, Column 3 of Table A3 analyzes firms' cash flows. Like with the prior effects, firm-specific shocks also positively affect the firm's cash flows (coefficient = 0.0266; t-statistic= 2.33).

Finally, I examine the robustness of the baseline analysis using an extend sample period. As explained in Section 2.3, I use 1995 as the starting point of the sample. To ensure that this choice does not affect the results, in Table A4, I repeat the same analysis used in Equation 7 but use the sample period from 1988 to 2015 (information on firms' cash flows is not available before 1988). Column 1 of Table A4 shows that this extension results in statistically stronger point estimates (coefficient = 0.0052; t-statistic = 3.64). Additionally, in Column 4 of Table A4, I drop cash flows from the regressors and extend the sample back to 1963. Again, I find a consistent result (coefficient = 0.0043; t-statistic = 4.43).

Together, these results provide supporting evidence that productivity shocks to the few largest firms in the economy eventually propagate to geographically close firms. These spillovers translate into higher earnings, higher sales, and higher cash flows among local non-dominant firms.

3.2 Dominant Firms and Intra-sector Non-Dominant Firms

Given the previous finding, I next examine the economic channels through which shocks to a dominant firm spillover to a geographically close non-dominant firm. So far, the literature has mainly focused on intra-sector and trade links between firms as a mechanism for propagation of shocks/information (e.g., Cohen and Frazzini (2008); Acemoglu et al. (2012)). Motivated by this evidence, I first examine the role of intra-sector links in propagating shocks from dominant firms to local non-dominant firms. Through these linkages, I expect to observe an economically stronger spillover effect when I restrict the sample to dominant and local non-dominant firms that operate in the same industry.

As expected, the results in Column 2 of Table 2 show that the geographic spillovers are economically stronger for non-dominant firms that share the same industry as the dominant firms (coefficient = 0.0202; t-statistic = 2.02).

Further, to ensure that the results are not sensitive to the above specification, instead of restricting the sample to dominant and intra-sector non-dominant firms, I use an *interaction term* to measure the impact of trade links on the geographic spillovers and run the following Fama and Macbeth (1973) regression:

$$\textit{Non-Dominant Firm's Shocks}_{j,t+1} = \alpha_j + \beta_1 \textit{ Dominant Firm's Shocks}_{j,t} + \beta_2 \textit{ Same Industry}_{j,t} + \beta_3 \textit{ Dominant Firm's Shocks}_{i,t} \times \textit{Same Industry}_{j,t} + \beta_4 X_{j,t} + \varepsilon_{j,t+1}. \tag{8}$$

Same Industry$_{j,t}$ is a dummy variable equal to 1 if, at time t, non-dominant firm j operates in the same sector as dominant firm i. The coefficient of interest, β_3, shows the geographic spillover of shocks from a dominant firm to an intra-sector non-dominant firm. The estimates (not reported) show a similar result as before: spillover effect is economically stronger for non-dominant firms that share the same sector with the dominant firms (coefficient = 0.0222; t-statistic = 1.79).[6]

Similar results hold in Column 5 of Table 2, when I use $\varepsilon_{j,i,s,t}$ (Regression 4) to measure firm-specific productivity shocks (coefficient = 0.0348; t-statistic = 2.55). Further, the results remain consistent when I perform the analysis using an extended sample period (see Columns 2 and 5 of Table A4).

These results identify the first economic channel (i.e., intra-sector linkages), through which productivity shocks to dominant firms spillover to other non-dominant firms. Although intra-sector links are an important economic channel for propagation of shocks, they may not be the only channel. I investigate propagation of shocks, beyond firms' trade links, in the next section.

3.3 Dominant Firms and Out-of-Sector Non-Dominant Firms

Dominant firms may affect other neighboring firms despite a lack of intra-sector connections. To further demonstrate this impact, I provide an example in Figure A1. The upper part of Figure A1 shows the effect of a negative shock to Sprint, a dominant U.S. company in the "Communication" industry that is headquartered in Kansas. This negative shock happened in 2005 and was followed by the merger of Sprint with Nextel. The merger was unsuccessful for Sprint because of many difficulties at the operational level. In the same year, Textron, a dominant U.S. firm in the "Aircraft" industry that is headquartered in Rhode Island, experienced a positive productivity shock, which was followed by a significant boost in its product demands.

As shown in Figure A1, Kansas non-dominant firms that operated outside of the communication industry considerably underperformed the market in 2005 and in 2006. Over the same period, non-dominant firms in Rhode Island, outside of the aircraft industry, outperformed the market. This example suggests that productivity shocks to dominant firms eventually propagate to other local firms, even in the absence of intra-sector connections.

[6] Untabulated results are available on request.

To empirically examine the above conjecture, I perform three tests. First, I study the shock spillover from dominant firms to out-of-sector non-dominant firms. Second, I study the effect of intra-market connections. Third and finally, I study the effects of customer-supplier connections on the main results.

3.3.1 Excluding Intra-sector Links

In Column 3 of Table 2, I restrict the sample to dominant and non-dominant firms that are headquartered in the same state but that operate in different industries. This restriction decreases the economic magnitude of the spillover to 33 bps. Despite this decline, the spillover of shocks from dominant firms to local non-dominant firms remains statistically significant (coefficient = 0.0033; t-statistic = 2.26). These results are not sensitive to how I categorize firms' industries. For instance, the estimates remain similar if I use Fama-French 5 industry portfolios to identify firm industries. Specifically, the coefficient is equal to 0.0044 (t-statistic = 1.91) when I use Fama-French 5 industry portfolios to identify firm industries.

As before, I check the robustness of the results using $\varepsilon_{j,i,s,t}$ to measure firm-specific productivity shocks. The results in Column 6 of Table 2 show similar outcome (coefficient = 0.0044; t-statistic = 6.47). Given that in each model using the shock measure from Equation 3 results in a more conservative point estimate, I use this measure for the rest of the analysis. Finally, I check the robustness of the above estimates using an extended sample period and again find consistent evidence (see Columns 3 and 6 of Table A4). This result provides supporting evidence that the geographic spillover of shocks from dominant to local non-dominant firms is not restricted to intra-sector connections only.

3.3.2 Excluding Product Market Links

One could argue that the standard industry classifications (such as SIC) do not precisely capture the scope of firms' business activities. To address this concern, I use the TNIC data from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). The TNIC data, which are based on firms' 10-K filings, provide a *score* that captures similarities between firms' product markets. Compared to SIC codes, TNIC data better classify firms that share a similar marketplace. Moreover, it reclassifies firms over time as companies' product markets evolve.

Using this measure, I extend the scope of companies' trade interactions from their industries to their mutual product markets. In particular, in Column 1 of Table 3, I exclude any pairs of dominant and non-dominant firms that, although not sharing the same industry, have a positive similarity *score*.[7] That is, I restrict the sample to dominant and local non-dominant firms that operate in different industries *and* have no overlaps in their product markets. This exclusion should remove any remaining interactions due to overlapping business operations between firms. The result in Column 1 of Table 3 shows the robustness of the previous findings to this restriction (coefficient = 0.0035; t-statistic = 2.65).

3.3.3 Excluding Customer-Supplier Links

In the previous sections, I used firms' industries and product markets to capture their trade links. However, through customer-supplier connections, firms might have trade links outside of their industries. Customer-supplier connections can exist between firms' sectors (Menzly and Ozbas (2010)) or directly between two firms (Cohen and Frazzini (2008)). These (out-of-sector) interactions can potentially confound the above conclusion that geographic shock spillover does not simply reflect firms' trade linkages. To address this concern, I identify different types of customer-supplier links (between firms and across their sectors) and study their effects on the baseline results.

First, I examine customer-supplier connections between firms' industries. To do so, I use the IO data from the "Benchmark Use Table" available from the BEA. The BEA provides updated information on IO data every 5 years. Similar to previous studies (e.g., Fan and Goyal (2006); Menzly and Ozbas (2010)), I use the information of 1997 for the period of 1995 to 1999, the information of 2002 for the period of 2000 to 2005, and the information of 2007 for the period after 2005. Following Fan and Goyal (2006), I identify dominant and non-dominant pairs with a *High IO* connection when the non-dominant firm's sector receives more than 5% of its total inputs from the dominant firm's industry. In Column 2 of Table 3, I exclude dominant and non-dominant firms that operate in the same sector, or have overlapping product market, or have a *High IO* connection between their sectors. As shown, the geographic spillover of shocks remains statistically significant even after this exclusion (coefficient = 0.0064; t-statistic = 2.74).

Next, I examine the role of direct customer-supplier links between firms. To this end, I use the customer-supplier data from Cohen and Frazzini (2008) to identify and exclude dominant and non-dominant pairs that, although not sharing a similar sector or marketplace, have a supplier (or customer) connection. That is, I restrict the sample to dominant and local non-dominant firms that operate in different industries, with no overlaps between their product markets and no customer-supplier connections. The estimates in Column 3 of Table 3 show

[7] I choose the *score* cutoff equal 0 to exclude dominant and non-dominant pairs that have any overlaps in their product markets, even when the overlap is small. The results, however, are not sensitive to this cutoff. For example, using a similarity *score* equal to 21.32% (like in Hoberg and Phillips (2016)), leads to a consistent point estimate of 0.0033 (t-statistic = 2.26).

that geographic spillover remains significant over and above the effects of direct customer-supplier links (coefficient = 0.0036; t-statistic = 2.68).

Given that firms are only required to report their major customers,[8] one could argue that the above identification may not completely capture firms' customer-supplier linkages. To address this concern, I additionally exclude dominant firms that operate in industries with a high level of out-of-sector interactions (i.e., dominant firms in services industries). In particular, I identify 17 industries in which firms have more than 80% of their customer-supplier links with companies outside of their own industries.[9] Subsequently, I repeat the analysis, excluding dominant firms that work in one of these sectors. As shown in Column 4 of Table 3, the results are also robust to this exclusion (coefficient = 0.0043, t-statistic = 2.11).

Overall, the evidence in this section suggests that the geographic spillover of shocks from dominant to local non-dominant firms is not exclusively driven by intra-sector (or trade) linkages between firms. Therefore, it is important to identify alternative economic channels through which shocks to dominant firms propagate.

3.4 Dominant Firms' Shock Spillovers Beyond Trade Links

Dominant firms considerably affect the economy of their headquarter states. Appendix B shows that productivity shocks to dominant firms explain a considerable portion of the local business cycles. For instance, productivity shocks to the only dominant firm in Nebraska (i.e., Union Pacific Railroad) explain more than 40% of the state's GDP growth. This local impact can subsequently aggregate and affect the national business cycle (as documented in Gabaix (2011)).

In Section 3.2, I showed that intra-section linkages between dominant and non-dominant firms are an economic channel through which productivity shocks to dominant firms propagate. However, trade links do not explain all shock spillovers. In this section, I investigate the *unexplained* part of the spillovers. That is, I focus on the sample of dominant and out-of-sector non-dominant firms and identify alternative economic channels that explain the propagation of shocks beyond firms' trade links.

[8] According to the SFAS No. 131 regulation, firms are required to report the identity of customers who account for more than 10% of their total sales.

[9] These sectors include construction materials; construction; electrical equipment; healthcare; personal services; consumer goods; restaurants, hotels, and motels; textiles; agriculture; precious metals; tobacco products; business supplies; printing and publishing; entertainment; shipbuilding, railroad equipment; shipping containers; and candy and soda.

3.4.1 Knowledge Externalities

That knowledge is relevant to economic growth is a well-documented finding in the economic literature (Carlino (1995)). Knowledge is an input of the production function (Döring and Schnellenbach (2006)) that positively affects firms' productivity growth (Kogan et al. (2017)). Moreover, knowledge tends to be localized and to spill over geographically (Jaffe et al. (1993); Wallsten (2001); Tappeiner et al. (2008)). Because of geographic proximity, managers and employees of firms near to an innovative company are assumed to have the advantage of being informed of a discovery before other firms. Nearby firms are also better equipped with the necessary knowledge to exploit innovation (Breschi and Lissoni (2001)).

Given the importance of knowledge to the economic growth of firms, I examine whether local usage of dominant firms' knowledge facilitates the geographic propagation of productivity shocks. Motivated by Jaffe et al. (2000), I use firms' patent data to proxy for their knowledge flow. In particular, I use patent data from Kogan et al. (2017) to measure the number of patents that each firm issues per year. Panels A and B of Table 1 report the average number of patents that dominant and non-dominant firms issue per year. Dominant firms, on average, issue 147 patents, whereas non-dominant firms issue less than 4 patents. Intel Business Machine and Microsoft, with the annual average of 3,100 and 1,500 patents, have the highest patent issuance among dominant firms.

I additionally account for the value of patents (Trajtenberg (1990)). To do so, I follow the Kogan et al.'s (2017) definition of *Citation-Weighted Patent*:

$$\textit{Citation-Weighted Patent}_{j,t} = \frac{\sum_{f \in P_{j,t}} (1 + C_f / \bar{C}_f)}{\textit{Book Assets}_{j,t}}, \tag{9}$$

where $P_{j,t}$ is the set of patents issued by firm j in year t. C_f shows the forward citations received by patent f, and $\bar{C}_f$ shows the average number of forward citations received by the patents granted in the same year as patent f. Controlling for firms' book assets ensures that *Citation-Weighted Patent* is not affected by the size fluctuations of firms. Table 1 shows that dominant firms also have a higher value of *Citation-Weighted Patent* compared to non-dominant firms (325 vs. 10).

Next, I examine whether knowledge externalities of the largest firms in the economy affect the geographic spillover of shocks. To this end, I perform two tests. For the first test, I use a state-level measure to examine whether a higher contribution of a dominant firm to the total innovation of its headquarter state leads to a stronger spillover effect. For the second test, I use a firm-level measure and examine whether a higher relevance of dominant firms' patents for local non-dominant firms leads to a stronger propagation of shocks.

I begin with the state-level measure. I calculate each dominant firm's contribution to the total number (or \$ value) of patents issued in its headquarter state as

$$Contribution\ to\ Local\ Knowledge_{i,t} = \frac{Number\ of\ Patents_{i,t}}{Total\ Number\ of\ Patents_{s,t}}, \tag{10}$$

and

$$Dollar\ Contribution\ to\ Local\ Knowledge_{i,t} = \frac{Citation\text{-}Weighted\ Patent_{i,t}}{Total\ \ Citation\text{-}Weighted\ Patent_{s,t}}, \tag{11}$$

where, $Total\ Number\ of\ Patents_{s,t}$ ($Total\ \ Citation\text{-}Weighted\ Patent_{s,t}$) shows the total number (\$ value) of patents issued in dominant firm i's headquarter state, at time t. I then run the following Fama and Macbeth (1973) regressions:

$$\begin{aligned} Non\text{-}Dominant\ Firm\text{'}s\ Shocks_{j,t+1} = \alpha_j + \beta_1\ \ Dominant\ Firm\text{'}s\ Shocks_{i,t} + \\ \beta_2\ \ Contribution\ to\ Local\ Knowledge_{i,t} + \\ \beta_3\ \ Dominant\ Firm\text{'}s\ Shocks_{i,t} \times Contribution\ to\ Local\ Knowledge_{i,t} + \beta_4\ X_{j,t} + \varepsilon_{j,t+1} \end{aligned} \tag{12}$$

and

$$\begin{aligned} Non\text{-}Dominant\ Firm\text{'}s\ Shocks_{j,t+1} = \alpha_j + \beta_1\ \ Dominant\ Firm\text{'}s\ Shocks_{i,t} + \\ \beta_2\ \ Dollar\ Contribution\ to\ Local\ Knowledge_{i,t} + \\ \beta_3\ \ Dominant\ Firm\text{'}s\ Shocks_{i,t} \times Dollar\ Contribution\ to\ Local\ Knowledge_{i,t} + \beta_4\ X_{j,t} + \varepsilon_{j,t+1}. \end{aligned} \tag{13}$$

In both regressions, β_3 is the coefficient of interest. Like in the previous analysis, I control for attributes that may affect non-dominant firms' productivity (i.e., $X_{j,t}$). Further, the sample is restricted to dominant and non-dominant firms that share the same headquarter state, but operate in different sectors.[10]

Column 1 of Table 4 shows the estimation results for Equation 12. All else equal, a dominant firm's productivity shocks have a stronger spillover impact, when the company accounts for a larger proportion of patents issued in its headquarter state (coefficient = 0.0063; t-statistic = 4.62). The results in Column 2 of Table 4 show a similar effect when I account for the dollar value of dominant firms' patents (coefficient = 0.0067; t-statistic = 4.21).

Next, I perform a firm-level analysis to investigate the impact of dominant firms' knowledge externalities on the geographic spillovers. In doing so, I first examine whether the

[10] The results stay consistent if in addition to intra-sector connections, I exclude dominant and local non-dominant firms with positive TNIC *score* and customer-supplier links.

spillover effect is stronger between dominant and local non-dominant firms with similar innovations. Every year, I identify dominant and non-dominant pairs that, although not sharing the same industry, have more than 20% overlap in the subclasses of their patents. If knowledge externalities of dominant firms are economically important, the spillover effect should be stronger between dominant and (out-of-sector) non-dominant firms with similar innovations. To test this conjecture, I run the following Fama and Macbeth (1973) regression:

$$\begin{aligned} \textit{Non-Dominant Firm's Shocks}_{j,t+1} &= \alpha_j + \beta_1 \textit{ Dominant Firm's Shocks}_{i,t} + \\ \beta_2 \textit{ Similar Subclass}_{j,t} + \beta_3 \textit{ Dominant Firm's Shocks}_{i,t} &\times \textit{Similar Subclass}_{j,t} + \\ &\beta_4 X_{j,t} + \varepsilon_{j,t+1}, \end{aligned} \tag{14}$$

where $\textit{Similar Subclass}_{j,t}$ is a dummy variable equal to 1, if at time t, dominant firm i and non-dominant firm j have more than 20% similarity in the subclasses of their patents. β_3, the coefficient of interest, shows the spillover of shocks from a dominant firm to a local non-dominant firm with high similarities in their innovations.

Consistent with the above conjecture, the estimates in Column 3 of Table 4 show that, all else equal, the geographic spillover of shocks is stronger between dominant and non-dominant firms with more than 20% match in the subclasses of their patents (coefficient = 0.1005; t-statistic = 2.24).[11]

Lastly, I study whether the spillover effects is stronger when a local non-dominant firm cite a dominant firm's patents more. Specifically, every year, I count the total number of times that local non-dominant firms cite patents from a dominant firm.[12] I then calculate the dominant firm's *Local Citations* as the ratio of total citations it receives from local non-dominant firms to the total citations received from all firms in the sample. Specifically,

$$\textit{Local Citations}_{i,t} = \frac{\textit{Total Citations from Local Non-Dominant Firms}_{i,t}}{\textit{Total Citations from All Frims}_{i,t}}. \tag{15}$$

A higher ratio of $\textit{Local Citations}_{i,t}$ captures a higher relevance of a dominant firm's knowledge for local non-dominant firms. Therefore, I expect a stronger spillover effect from a dominant firm that has a higher measure of *Local Citations*.

[11] The results are not sensitive to the 20% cutoff. For example, the point estimate of β_3 in Regression 14 is equal to 0.1687 (t-statistic = 2.87), and 0.0590 (t-statistic = 2.93) when I use a 10% or 30% cutoff to identify dominant and non-dominant firms with same-subclass patents.

[12] For instance, in 1995, the Walt Disney company (headquartered in California) issued a patent (number: 5405152) that introduced physical feedback in interactive video games. Later, the Immersion Corporation (also headquartered in California), which develops haptic technologies, used the Walt Disney's patent in over 130 of its own patents. For example, Immersion used Walt Disney's idea in developing a new patent (number: 6686911) that allowed force feedback in control knobs.

The estimate results in Column 4 of Table 4 provide supporting evidence for the above conjecture. All else equal, shocks to dominant firms, whose patents are mostly cited by local non-dominant, create a stronger spillover effect (coefficient = 0.0407; t-statistic = 1.84). Together, these results confirm the role of dominant firms' knowledge externalities as an economic channel that facilitates the propagation of productivity shocks from dominant firms, over and above intra-sector linkages.

3.4.2 State Income Taxes

Next, I study the role of state income taxes as an additional economic channel for the propagation of dominant firms' productivity shocks. State income tax payments made by dominant firms are a financial source of income for the firms' local government. For example, according to Delta Airline's website, in 2013, the company paid over $300 million to Georgia's government through taxes and fees. Local governments use taxes to assist and subsidize local firms and to develop the infrastructure for their local economies. This development can positively affect the growth opportunities of local firms (Firebaugh and Beck (1994); Levine (1997)). Therefore, through the tax channel, I expect stronger spillover effects in states in which dominant firms pay a higher proportion of state income taxes.

To test the above hypothesis, I first show that an increase in a state's tax budget, leads to a higher productivity growth for local firms. In doing so, I measure the annual change in states' tax budgets as

$$Income\ Tax\ Rate_{s,t} = \frac{Income\ Taxes_{s,t} - Income\ Taxes_{s,t-1}}{Income\ Taxes_{s,t-1}} \tag{16}$$

I then define a dummy variable, $Income\ Tax\ Increase_{s,t}$, equal to 1, if at time t, state s has a positive $Income\ Tax\ Rate$. Next, I run the following pooled-panel regression:

$$\textit{Non-Dominant Firm's Shocks}_{j,t+1} = \alpha_j + \beta_1\ Income\ Tax\ Increase_{s,t} + \beta_2\ X_{j,t} + \delta_t + \gamma_s + \varepsilon_{j,t+1}. \tag{17}$$

To control for the heterogeneous effects of local taxes across states and over time, I include year (δ_t) and state (γ_s) fixed effects in the analysis. If an increase in a state's income tax budgets positively affects productivity of its local firms, I expect β_1 from the above regression to be positive and significant. The results in Column 1 of Table 5 confirms this conjecture: in states with an increase in their income tax budgets, local firms experience a 4-percentage-point increase in their future productivity shocks (coefficient = 0.0375; t-statistic = 1.75).

Given the influence of local tax budgets on productivity of local firms, I next investigate whether a higher contribution of dominant firms to local tax budgets leads to stronger shock spillovers. To do so, I collect the amount of dominant firms' state income taxes from Compustat ($Income\ State\ Tax_{i,t}$). The available tax information shows *payable* income taxes. Therefore, this information may not precisely capture firms' tax payments because firms may receive tax credits from their local governments. Therefore, I use the proportion of actual tax paid ($Total\ Tax\ Paid_{i,t}$) over the total payable income taxes ($Total\ Income\ Tax_{i,t}$) to proxy for the income taxes dominant firms pay to their local governments. Specifically, I measure a dominant firm's state income taxes as

$$State\ Tax_{i,t} = \frac{Total\ Tax\ Paid_{i,t}}{Total\ Income\ Tax_{i,t}} \times Income\ State\ Tax_{i,t}. \tag{18}$$

Subsequently, I run the following Fama and Macbeth (1973) regression:

$$\begin{aligned} Non\text{-}Dominant\ Firm\text{'s}\ Shocks_{j,t+1} = \alpha_j + \beta_1\ Dominant\ Firm\text{'s}\ Shocks_{i,t} + \beta_2\ State\ Tax_{i,t} + \\ \beta_3\ Dominant\ Firm\text{'s}\ Shocks_{i,t} \times State\ Tax_{i,t} + \beta_4\ X_{j,t} + \varepsilon_{j,t+1}. \end{aligned} \tag{19}$$

β_3 is the coefficient of interest that shows the effect of a dominant firm's state income taxes on its shock spillover to a local non-dominant firm. The results in Column 2 of Table 5 confirm the role of the tax channel in the spillover of productivity shocks. All else equal, in states in which dominant firms pay a higher amount of state income taxes, local non-dominant firms experience a more substantial shock spillover (coefficient = 0.0074; t-statistic = 2.23).

Using nominal taxes (like in Equation 18) can potentially ignore the size differences between states' economies. For instance, a dollar payment made by Apple to the state of California may have a different local impact compared with the same amount paid by Union Pacific to the state of Nebraska. To address this concern, I create two additional tax measures. For the first measure, I adjust $State\ Tax_{j,t}$ (from Equation 18) to the total corporate income taxes generated in a dominant firm's headquarter state:

$$Contribution\ to\ Local\ Corporate\ Income\ Taxes_{i,t} = \frac{State\ Tax_{i,t}}{Total\ Corporate\ Income\ Taxes_{s,t}}. \tag{20}$$

Next, I repeat the same analysis of Regression 19, replacing $State\ Tax_{i,t}$ with the above measure. The results in Column 3 of Table 5 shows consistent outcome. The shock spillovers are economically stronger when a dominant firm accounts for a larger proportion of corporate income taxes in its headquarter state (coefficient = 0.0130; t-statistic = 2.06).

One could argue that accounting only for corporate income taxes (like in Equation 20) ignores the effect of private firms. Specifically, income tax payments of dominant firms, although large compared to other public firms, may be negligible compared to the tax payments of local private firms. To address this concern, I additionally incorporate the effect of total income taxes (from all sources) and adjust dominant firms' state tax payments by the total incomes taxes generated in their headquarter states. Specifically,

$$Contribution\ to\ Local\ Income\ Taxes_{i,t} = \frac{State\ Tax_{i,t}}{Total\ Income\ Taxes_{s,t}}. \tag{21}$$

Column 4 of Table 5 show the estimates using the above measure. As shown controlling for states' total income taxes results in a consistent outcome (coefficient = 0.0072; t-statistic = 2.59).[13] Together, the analyses in Sections 3.4.1 and 3.4.2 identify economic channels that cause propagation of shocks from the largest firms in the economy, beyond direct trade links.[14]

3.5 Robustness Checks and Alternative Explanations

In this section, I provide additional robustness checks to examine possible alternative explanations for the main results.

3.5.1 Economic Activities of Dominant Firms in Their Corporate Headquarters

So far, I have used firms' headquarter states to identify the geographic networks between dominant and non-dominant firms. This choice is guided by the availability of macro-level data (such as income taxes) at the state level. Firms, however, may have a different level of economic activity in their headquarter states (Bernile et al. (2016); Addoum et al. (2017)). For instance, a dominant firm, such as Walmart, mostly operates outside of its headquarter state, whereas the economic activities of some dominant firms, such as Winn-Dixie, are concentrated in their local areas. To investigate how dominant firms' activities in their headquarter states affect the baseline results, I account for the economic presence of dominant firms in their headquarter states, using *Citation Share* data from Bernile et al. (2016).

From 1994 to 2012, for each firm year, Bernile et al. (2016) parse the 10-K filings and count the number of times references are made to each economic center of the firm. Using this information, I create a *Citation Share* measure: the number of times a state is cited,

[13] Some states may have missing information on total income taxes. For this reason, the number of observations in Column 4 of Table 5 is different from those in Columns 2 and 3.

[14] in Table A5, I investigate the dynamic effect of dominant firms' state taxes. It is possible that the development of local infrastructures takes more than 1 year. Therefore, the local effect of dominant firms' taxes also should be salient years after the payments. To test this hypothesis, I repeat the same analysis used in Equation 19 but use $state\ tax_{t-1}$ and $state\ tax_{t-2}$. Consistent with the above conjecture, the results of Table A5 show that the effects of a dominant firms' state income taxes remain statistically and economically significant 3 years after the firm's payment (coefficients = 0.086 and 0.0116; t-statistic = 2.28 and 3.15).

divided by the total number of citations of all U.S. states in a firm's 10-K filing. Subsequently, I restrict the sample to dominant and non-dominant firms that have the highest economic activity in their headquarter states (i.e., their headquarter states have the top-rank *Citation Share* compared to other states). Given that this restriction identifies firms that have a higher level of economic activities in their local areas, I expect to observe a stronger geographic spillover of shocks.

Column 1 of Table 6 provides supporting evidence for the above conjecture. As expected, the geographic spillover of shocks increases to 69 bps (coefficient = 0.0069; t-statistic = 3.18), which, compared to the baseline estimate, is economically and statistically more significant.

Further, I use an alternative measure of geographic proximity of dominant and non-dominant firms. In particular, I repeat the baseline analysis using MSAs to identify firms' geographic networks. Given that MSAs identify firms in close geographic proximity, I expect a stronger spillover of shocks among firm pairs in the same MSA. The results in Table A6 provide supporting evidence for this conjecture. The economic magnitude of spillovers increases to 1.4 percentage points when I use MSAs to identify firms' local economies (coefficient = 0.0141; t-statistic = 2.15).

3.5.2 Effects of Common Local Shocks

One could argue that the documented spillover of shocks from dominant firms to out-of-sector non-dominant firms is mainly driven by the state-level common shocks. For example, it is possible that dominant firms—compared to non-dominant firms—respond faster to a common local shock. The common local shock, therefore, may drive the positive correlation between shocks to dominant firms and next year shocks to local non-dominant firms.

Although in the second measure of firm-level shocks (i.e., $\varepsilon_{j,i,s,t}$ from Regression 4) I control for the impact of state-level productivity growth, I perform additional tests to ensure that the results using the first measure of shocks (i.e., Equation 2) are not affected by common local shocks. To do so, I repeat the baseline analysis and adjust firms' productivity shocks by de-meaning their productivity growth from the average productivity growth of firms in the same headquarter state. This de-meaning procedure identifies firm-level productivity shocks over and above the influence of state-level shocks. In particular, I use the following proxy:

$$Productivity\ Shocks_{j,t} = Productivity\ Growth_{j,t} - \frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,s,t}, \quad (22)$$

where N shows the total number of firms headquartered in state s. As shown in Column 2 of Table 6, adjusting for state-level shocks results in a consistent outcome (coefficient = 0.0084; t-statistic = 4.62). Further, the results remain consistent when I de-mean each explanatory variable from its within-the-state average value. In this case, the point estimate (not tabulated) is equal to 0.0021 (t-statistic = 2.68).[15]

I perform two additional tests to investigate the impact of common local shocks. First, I use the suggested framework in Dougal et al. (2015). As argued by Dougal et al. (2015), one way to rule out the effect of common shocks is to use a setup in which shocks are mainly generated by a *small group* of firms. Motivated by this argument, I focus on the sample of states with a maximum of four dominant firms throughout the sample.[16] As expected, the results in Column 3 of Table 6 show that this restriction increases the economic magnitude of the baseline effects to 2 percentage points (coefficient = 0.0203; t-statistic = 2.07).

Second, in an untabulated result, I control for the impact of state-level common shocks using the states' *Economic Activities* index from Korniotis and Kumar (2013). This index controls for the economic condition of states over time and is equal to the sum of state-level income growth and housing collateral ratio, minus the standardized value of the relative unemployment ratio. Controlling for this index also results in a consistent geographic spillover.

3.5.3 Propagation of Shocks across Industries

An alternative explanation for the baseline results (in Table 2) is the propagation of productivity shocks across industries (Menzly and Ozbas (2010)). For example, it is possible that, because of a positive shock to the tech industry, employees of Apple (as a dominant firm in the tech industry) experience a higher level of salary and, subsequently, spend that money to receive services from firms that are outside the tech industry. Therefore, the positive shock (which is not caused by Apple) transfers to other out-of-sector firms. Although the possibility of shock propagation, due to sectoral connectivity (as documented in Foerster et al. (2011)), is not in conflict with the main motivation of this study, it raises a concern in the *causality* argument in Table 2.

To address this concern, I use an alternative proxy for firms' productivity shocks. I de-mean firms' productivity growth from the average growth of firms that operate in the

[15]The results also remain similar when I adjust firms' shocks to the effect of common shocks within the same state and industry. In particular, using $Productivity\ Shocks_{j,t} = Productivity\ Growth_{j,t} - \frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,i,s,t}$, where $\frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,i,s,t}$ shows the average productivity growth of firms in the same state and industry results in a point estimate of 0.0023 (t-statistic = 2.21). This result confirms that shock spillover from dominant firms to out-of-sector non-dominant firms is not merely driven by the impact of common local (and industry) shocks.

[16]These states are shown in Column 2 of Table B1.

same industry. In this way, I identify firm-level productivity shocks over and above common industry shocks. Specifically, I use the following proxy:

$$Productivity\ Shocks_{j,t} = Productivity\ Growth_{j,t} - \frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,i,t}, \quad (23)$$

where $\frac{1}{N}\sum_{j=1}^{N} Productivity\ Growth_{j,i,t}$ shows the average productivity growth of firms among the top-100 firms in sector i. Column 4 of Table 6 repeats the baseline analysis using the new proxy. Adjusting for the industry-level shocks does not affect the baseline results (coefficient = 0.0057; t-statistic = 2.05).

3.5.4 Alternative Measure of Firm Productivity

Additionally, I examine the robustness of the baseline results to an alternative measure of productivity. To this end, I use firm-level total factor productivity (TFP) data from İmrohoroğlu and Tüzel (2014). In particular, 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)

$$y_{j,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + w_{i,t} + \eta_{i,t}. \quad (24)$$

Using this information, I re-estimate firms' productivity shocks following the same method described in Section 2.2.1. Column 5 of Table 6 shows that using TFP as a measure of firms' productivity leads to a consistent point estimate (coefficient = 0.0033; t-statistic = 2.35).

3.5.5 Aggregating Dominant Firms' Productivity Shocks

As explained in Section 2.3, to form the panel, for each dominant firm in the sample, I identify all of the available non-dominant firms headquartered in the same state. This identification raises the concern of biased estimation, because of the repeated values in the pooled panel. I choose Fama and Macbeth (1973) regressions to mitigate this possibility, but to ensure that the results are not affected by this concern, I repeat the baseline analysis by aggregating the main independent variable (i.e., dominant firms' productivity shocks). In doing so, I first calculate the weighted average of dominant firms' shocks as

$$\Gamma_{s,t} = \sum_{j=1}^{K} \frac{Sales_{i,t-1}}{GDP_{t-1}} \times Productivity\ Shocks_{i,t}, \quad (25)$$

where K shows the total number of dominant firms in a state. Next, I run the following Fama and Macbeth (1973) regression:

$$\textit{Non-Dominant Firm's Shocks}_{j,t+1} = \alpha_j + \beta_1\ \Gamma_{s,t} + \beta_2\ X_{j,t} + \varepsilon_{j,t+1}. \tag{26}$$

Column 6 of Table 6 reports the regression results. As shown, this aggregation does not affect the outcome (coefficient = 0.032; t-statistic = 2.29). The same result (not tabulated) holds when I run Equation 26 on the sample of dominant and local non-dominant firms that operate in different sectors.

3.5.6 Excluding States with a High Agglomeration of Dominant Firms

Additionally, I study whether geographic spillovers are primarily driven by states with a high agglomeration of dominant firms. To do so, I exclude New York, California, Texas, and Illinois, which have the highest number of dominant firms (see Figure 1).

Column 7 of Table 6 shows the results that exclude these states. This restriction does not decrease magnitude of spillover. On the contrary, it intensifies the economic magnitude to 73 bps (coefficient = 0.0073; t-statistic = 2.15). This increase potentially reflects the effects of shock diversification in the excluded states.

3.5.7 Excluding Merger Activities

Next, I study the effect of merger activities on the baseline analysis. Firms' merger activities can potentially affect their net sales and number of employees for reasons other than productivity. To ensure that the results are not affected by merger activities, every year, I identify and exclude dominant and non-dominant firms that have reported a merger activity. The results in Column 8 of Table 6 show that the baseline analysis is unaffected by mergers (coefficient = 0.0048; t-statistic = 2.47).

3.5.8 Effects of 2008 Financial Crisis

Finally, I investigate whether the shock spillovers are driven by the impact of the recent financial crisis. One could argue that the 2008 nation-wide crisis of financial institutions, lead local and small banks to be constrained. This possibility could potentially suppress revenue growth of local non-dominant firms with a lag. To empirically rule out this channel, I repeat the analysis by restricting the sample to periods before 2008. If the spillover effect is primarily driven by the above channel, β_1 from Regression 7 should be statistically insignificant, in periods prior to the financial crisis. Contrary to this conjecture, the estimates in Column

9 of Table 6 shows point estimates similar to the baseline analysis (coefficient = 0.0042; t-statistic = 2.19).[17]

4 Dominant Firms' Shock Spillovers and Asset Prices

Productivity shocks to dominant firms contain information about the future fundamentals of other firms, so they should be priced in the market. In this section, I study whether different groups of investors incorporate the systematic information contained in dominant firms' productivity shocks. To do so, I examine the behavior of market participants and equity analysts.

4.1 Baseline Analysis

If stock prices underreact because the value-relevant information in dominant firms' productivity shocks aggregates with a delay, stock prices should be predictable. To test this prediction, I develop a set of trading strategies that exploit the slow diffusion of geographically dispersed information contained in dominant firms' shocks. I form the baseline trading strategy by sorting the U.S. states on the weighted average of dominant firms' shocks (Equation 25) headquartered in the state. Specifically, I sort states into deciles (Jegadeesh et al. (2004)), where the tenth decile contains states with the highest (i.e., most positive) weighted average of dominant firms' shocks, and the first decile contains states with the lowest (i.e., most negative) weighted average of dominant firms' shocks. Subsequently, I create a zero-cost portfolio that goes long on all non-dominant firms headquartered in the tenth decile states and short on all the non-dominant firms headquartered in the states of the first decile. Following Fama and French (1993), to ensure the information related to dominant firms' productivity shocks for year $t-1$ is known to market participants, portfolios' returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$.

Panel A of Table 7 reports the main characteristics of the non-dominant firms in each decile. As shown, firms in each group have similar average monthly excess returns, ranging from 0.55% to 1.23%, with the standard deviations between 6.49% to 7.37%. The market share of each group ranges from 0.80% to 2.64%, confirming that a small group of firms (i.e., dominant firms) make up a considerable portion of the overall market capitalization (Malevergne et al. (2009)). Portfolios are also evenly distributed among the U.S. states. The long-short portfolio has a monthly average excess return of 0.44% with a standard deviation of 2.68%. It forms 5.28% of the total market shares and covers 18.78% of the U.S. states.

[17]The point estimates in the post-crisis period is equal to 0.0059 (t-statistic = 1.61).

Panel B of Table 7 presents the risk-adjusted performance (i.e., alpha) of the trading strategy. Specifically, I use the following factors: (1) the capital asset pricing (CAPM) model, which uses the market excess return (MKT); (2) the Fama and French (1993) three-factor model, which includes market (MKT), size (SMB), and value (HML) factors; (3) the Carhart (1997) four-factor model, which adds the momentum factor (UMD), and (4) the Pastor and Stambaugh (2003) five-factor model that additionally includes the liquidity factor (LQT). The performance of the long-short portfolio remains statistically and economically significant when including the various factors. In particular, the monthly CAPM, three-, four-, and five-factor alphas are 0.425% (t-statistic = 2.48), 0.414% (t-statistic = 2.46), 0.320% (t-statistic = 1.92), and 0.373% (t-statistic = 2.17), respectively.

Overall, the baseline trading strategy suggests that the market does not fully extract the information contained in dominant firms' productivity shocks. This leads to an annual risk-adjusted performance of 5.4%. The result remains consistent when I use a value-weighted long-short portfolio. More precisely, in Panel C of Table 7, I repeat the same trading strategy using firms' previous month's market capitalizations as the weighting matrix. The results indicate an even higher abnormal monthly return of 0.605 bps (i.e., 7.51% annual return). Specifically, the monthly CAPM, three-, four-, and five-factor alphas are 0.719% (t-statistic = 2.30), 0.689% (t-statistic = 2.37), 0.595% (t-statistic = 2.11), and 0.605% (t-statistic = 2.04), respectively for the value-weighted analysis. This economic magnitude is comparable to the effect documented in Menzly and Ozbas (2010).[18]

Next, I examine whether documented price underreaction increases when the effects of dominant firms on non-dominant firms are less salient. To test this hypothesis, I repeat the previously explained trading strategy on the sample of local non-dominant firms that (1) operate in a different industry than do the dominant firms and (2) share the same industry as the dominant firms.

Panel D (E) of Table 7 reports the risk-adjusted performance of the long-short portfolio using the former (latter) sample. The results show that the documented positive alphas are primarily driven by the market's underreaction to the effects of dominant firms on out-of-sector non-dominant firms. As shown in Panels D and E of Table 7, restricting the sample to non-dominant firms that share the same industry as the dominant firms results in statistically insignificant alphas in the four- and five-factor specifications.

[18] In Appendix A, I further study the time it takes the information in dominant firms' productivity shocks to be incorporated into stock prices. To do so, I re-examine the performance of the explained long-short portfolio K months after forming the portfolio. Figure A2 shows the diffusion pattern of the unpriced information. The risk-adjusted alpha of the long-short portfolio (using the five-factor model) stays statically significant through the first 7 months after creating the portfolio. This result suggests that, on average, it takes 7 months for the market to realize the economic impact that dominant firms' productivity shocks have on other local firms.

4.2 Double-Sorted Portfolios

In this section, I further investigate the slow diffusion of information contained in dominant firms' productivity shocks using a double-sorted portfolio analysis. Specifically, I repeat the baseline trading strategy, but additionally sort non-dominant firms on the sensitivity of their returns to those of local dominant firms. Each month, I run the following rolling regression, with a thirty-six-month rolling window (Bernile et al. (2015)):

$$\begin{aligned} Excess\ Return_{i,t} = \alpha + \beta_1\ Market\ Excess\ Return_t + \\ \beta_2\ Dominant\ Firms'\ Excess\ Return_t + \varepsilon_{i,t}. \end{aligned} \tag{27}$$

Above, $Excess\ Return_{i,t}$ shows the monthly excess return of non-dominant firm i. $Market\ Excess\ Return_t$ is the monthly excess return for the value-weighted market portfolio. $Dominant\ Firms'\ Excess\ Return_t$ shows the monthly excess return for the value-weighted portfolio of dominant firms, that are headquartered in the same state as the non-dominant firm.

Using the prior month's estimates of β_2, I sort non-dominant firms in two groups: (1) *High-beta* non-dominant firms, as those with above-the-median β_2s, and (2) *Low-beta* non-dominant firms, as those with below-the-median β_2s. If the positive alphas in Table 7 are primarily driven by the slow diffusion of information contained in dominant firms' shocks, the price underreaction should be more salient among the *High-beta* non-dominant firms. To test this conjecture, I perform a double-sorted analysis where I independently sort non-dominant firms on the exposure of their monthly returns to those of local dominant firms (i.e., β_2 from Regression 27) and the weighted average of dominant firms' shocks in their headquarter states (similar to Section 4.1).

Table 8 shows the double-sorted results for the 2 $\times$ 10 portfolios. Consistent with the above hypothesis, Panel A of Table 8 shows that the monthly excess return of the long-short portfolio is higher among the *High-beta* non-dominant firms (0.74% vs 0.11%). The 63 bps difference in portfolios' excess returns is statistically significant at the 5% level (t-statistic = 2.23).

The same result holds when I perform risk-adjusted analysis. The estimates in Panel B of Table 8 show that, in each risk-adjusted model, the alpha of the double-sorted long-short portfolio is economically and statistically stronger for the *High-beta* non-dominant firms. In particular, the monthly CAPM, three-, four-, and five-factor alphas are 0.743% (t-statistic = 3.05), 0.718% (t-statistic = 3.10), 0.595% (t-statistic = 2.57), and 0.597% (t-statistic = 2.57), respectively for the non-dominant firms with higher betas. However, in all risk-adjusted models, the alphas are statistically insignificant for the low-beta non-dominant firms.

Finally, I investigate the role of intra-sector connections on the risk-adjusted return of the long-short portfolios. Consistent with the results in Table 7, the estimation results in Panels C and D of Table 8 show that the positive alphas in Panel B are mainly driven by the market's inattention to the economic links between dominant and non-dominant firms, beyond intra-sector links. Overall, these results suggest that the market is not able to fully react to the impact that the largest firms in the economy have on other local businesses. This underreaction further increases when firms' connections are less salient to investors or when returns of local businesses have a higher exposure to dominant firms' returns.

4.3 Dominant Firms' Shock Spillovers and Analysts' Behavior

In last set of analysis, I study whether sell-side equity analysts, as a group of sophisticated agents, incorporate the information contained in dominant firms' shocks. To do so, I investigate whether lagged shocks of dominant firms significantly affect forecasts and accuracy of analysts, when they issue earnings forecasts for non-dominant firms. Specifically, I run the following Fama and Macbeth (1973) regression:

$$Forecast\ Errors_{a,j,t} = \alpha + \beta_1\ \textit{Dominant Firm's Shocks}_{i,t-1} + \beta_2\ X_{j,t} + \beta_3\ Z_{a,t} + \varepsilon_{a,j,t}. \quad (28)$$

The dependent variable is the annual average of analyst a's quarterly *forecast errors* for non-dominant firm j. The main coefficient of interest is β_1, which captures the analyst's reaction to the lagged shocks from dominant firm i. In addition to firm control variables (i.e., $X_{j,t}$), I include analyst attributes ($Z_{a,t}$), including the analyst's *Brokerage Size* (Gu and Wu (2003) and Lim (2001)), *Experience* (Hong and Kubik (2003)), *Location* (Malloy (2005)), *All-star* position (Desai et al. (2015)), excess information about dominant firms (*Both-cover*), and *Forecast Age* (Agrawal et al. (2006)).

Table 9 reports the estimation results. In Panel A, I use the sample of non-dominant firms that share the same industry and headquarter state as the dominant firm. The results in Column 1 indicate that a higher level of dominant firms' shocks results in a higher level of optimism in analysts' earnings forecasts, when they issue forecasts for local non-dominant firms (coefficient = 0.0234; t-statistic = 4.26). To examine this further, I separate out the impact of dominant firms' positive and negative shocks in Columns 2 and 3. As shown, the increase in analysts' bias is mainly driven by dominant firms' positive shocks. That is, analysts are more likely to issue optimistic earnings forecasts for intra-sector non-dominant firms when local dominant firms experience positive productivity shocks (coefficient = 0.0146; t-statistic = 2.94). This result is in line with the results of previous studies (Daniel et al. (1998); Easterwood and Nutt (1999)) that analysts react overly optimistic to positive news.

Given that productivity shocks and forecast errors are signed variables, in Columns 4 to 6 of Table 9, I repeat the same analysis, using analysts' accuracy as the main independent variable. Specifically, I run the following Fama and Macbeth (1973) regression:

$$Accuracy_{a,j,t} = \alpha + \beta_1 \ \ Dominant\ Firm\text{'}s\ Shocks_{i,t-1} + \beta_2\ X_{j,t} + \beta_3\ Z_{a,t} + \varepsilon_{a,j,t}. \tag{29}$$

In the above equation, accuracy is the absolute value of the analyst's forecast errors. Therefore, a lower value of the variable shows a higher level of accuracy. Consistent with the previous results, the accuracy results also suggest that analysts earnings forecasts for local non-dominant firms are less accurate in response to lagged positive shocks to dominant firms in the same sector (coefficient = 0.0064; t-statistic = 1.12). However, forecasts of analysts for non-dominant firms are closer to the actual earnings, when analysts account for the information content of negative productivity shocks to local dominant firms (coefficient = -0131; t-statistic = -3.59). These results suggest that analysts respond to shocks to the largest U.S. firms, when they issue earnings forecasts for other intra-sector non-dominant firms.

Next, I examine whether analysts also account for the impact of dominant firms on out-of-sector non-dominant firms. To do so, in panel B of Table 9, I restrict the sample to dominant and non-dominant firms that are headquartered in the same state, but operate in different sectors. As shown, unlike the estimation results in Panel A, in all specifications dominant firms' productivity shocks (positive or negative) load insignificantly on analysts' earnings forecasts and accuracy. These result suggest that, even equity analysts do not fully incorporate the impact that the largest firms in the economy may have on local firms, beyond trade links.

The evidence in Panel B of Table 9 speaks to the geographic momentum. Parsons et al. (2016) note that an increase in analysts' coverage does not affect the geographic lead-lag effect. Authors have concluded that because analysts are most likely specialized in some industries, they might not be aware of the geographic effects that firms have on each other. The findings in this section provide empirical evidence for this conjecture. Overall, the results suggest that, in addition to industry-related skills, analysts could benefit from paying attention to information that highly depends on the geography of firms.

5 Summary and Conclusions

In this paper, I have examined the mechanism through which productivity shocks to the largest U.S. firms (i.e., dominant firms) aggregate to affect the national business cycle. Focusing on geographic networks, I find evidence of shock spillovers from dominant to local non-dominant firms. Productivity shocks to non-dominant firms subsequently affect local firms' earnings, sales, and cash flows. The results indicate that intra-sector trade links are an important economic channel for spillover. However, spillover effects by geographical area are not restricted to trade linkages between firms. I show evidence of the role of knowledge externalities and state income taxes of dominant firms as alternative channels for geographic spillovers.

Next, I studied whether the market understands these spillovers. To do this, I formed a series of geographic trading strategies. A zero-cost portfolio that goes long on non-dominant firms in states with the highest shocks to dominant firms and goes short on non-dominant firms in states with the lowest shocks to dominant firms generates a positive monthly alpha of 44 bps, that is, 5.4% annualized risk-adjusted excess performance. Moreover, a more sophisticated group of the market's agents (i.e., equity analysts) also do not fully react to this source of information.

Overall, the results in this paper provide a mechanism for the macro-level evidence in Gabaix (2011). Furthermore, the identified channels offer a fuller picture of how firms affect each other beyond intra-sector or direct trade links. The economic impact of dominant firms on the national and local economies and the direct effects of these firms on the local businesses can be a useful source of information for equity analysts and for investors evaluating firms' fundamentals.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5):1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2016). Networks, Shocks, and Systemic Risk. *The Oxford Handbook of the Economics of Networks*, pages 569–607.

Addoum, J. M., Kumar, A., and Law, K. K. F. (2017). Slow Diffusion of State-Level Information. *Working Paper*.

Agrawal, A., Chadha, S., and Chen, M. A. (2006). Who is Afraid of Reg FD? The Behavior and Performance of Sell- Side Analysts Following the SEC's Fair Disclosure Rules. *Journal of Business*, 79(6):2811–2834.

Antoniou, C., Kumar, A., and Maligkris, A. (2016). Terrorist Attacks, Analyst Sentiment, and Earnings Forecasts. *Working Paper*.

Bali, T. G., Engle, R. F., and Murray, S. (2016). Empirical Asset Pricing: The Cross Section of Stock Returns. *Wiley, ISBN: 978-1-118-09504-1*.

Baqaee, D. R. and Farhi, E. (2017). The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem. *Working Paper*.

Bernile, G., Korniotis, G. M., Kumar, A., and Delikouras, S. (2016). Geography of Firms and Propagation of Local Economic Shocks. *Working Paper*.

Bernile, G., Kumar, A., and Sulaeman, J. (2015). Home away from Home: Geography of Information and Local Investors. *Review of Financial Studies*, 28(7):2009–2049.

Biswas, S., Chakraborty, I., and Hai, R. (2017). Income Inequality, Tax Policy, and Economic Growth. *Economic Journal*, 127:688–727.

Bondt, W. F. M. D. and Thaler, R. H. (1990). Do Security Analysts Overreact? *American Economic Association*, 80(2):52–57.

Breschi, S. and Lissoni, F. (2001). Knowledge Spillovers and Local Innovation Systems: A Critical Survey. *Industrial and Corporate Change*, 10(4):975–1005.

Carhart, M. M. (1997). On Persistence In Mutual Fund Performance. *Journal of Finance*, 52(1):57–82.

Carlino, G. A. (1995). Do Education an Training Lead to Faster Growth in Cities? *Federal Reserve Bank of Philadelphia Business Review*, January/February:15–22.

Cochrane, J. H. (1994). Shocks. *Carnegie-Rochester Conference Series on Public Policy*, 41:295–364.

Cohen, L. and Frazzini, A. (2008). Economic Links and Predictable Returns. *Journal of Finance*, 63(4):1977–2011.

Cohen, L., Frazzini, A., and Malloy, C. (2010). Sell-Side School Ties. *Journal of Finance*, 65(4):1409–1437.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, 53(6):1839–1886.

DellaVigna, S. and Pollet, J. (2009). Investor Inattention, Firm Reaction, and Friday Earnings Announcements. *Journal of Finance*, 64(2):709–749.

Desai, H., Liang, B., and Singh, A. K. (2015). Do All-Stars Shine? Evaluation of Analyst Recommendations. *Financial Analysts Journal*, 56(3):20–29.

Dougal, C., Parsons, C. A., and Titman, S. (2015). Urban Vibrancy and Corporate Growth. *Journal of Finance*, 70:163–210.

Döring, T. and Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature. *Regional Studies*, 40(3):375–395.

Easterwood, J. C. and Nutt, S. R. (1999). Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism? *Journal of Finance*, 54(5):1777–1797.

Fama, E. F. and French, K. R. (1993). Common Risk Factors In The Returns On Stocks And Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and Macbeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3):607–636.

Fan, J. P. H. and Goyal, V. K. (2006). On the Patterns and Wealth Effects of Vertical Mergers. *Journal of Business*, 79(2):877–902.

Firebaugh, G. and Beck, F. D. (1994). Does Economic Growth Benefit the Masses? Growth, Dependence, and Welfare in the Third World. *American Sociological Review*, 59(5):631.

Foerster, A. T., Sarte, P.-D. G., and Watson, M. W. (2011). Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production. *The Journal of Political Economy*, 119(1):1–38.

Frank, M. Z. and Goyal, V. K. (2009). Capital structure decisions: Which factors are reliably important? *Financial Management*, 38(1):1–37.

Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica*, 79(3):733–772.

Gu, Z. and Wu, J. S. (2003). Earnings Skewness And Analyst Forecast Bias. *Journal of Accounting and Economics*, 35(1):5–29.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2011). Limited Investor Attention and Stock Market Misreactions to Accounting Information. *Review of Asset Pricing Studies*, 1(1):35–73.

Hirshleifer, D. and Teoh, H. (2003). Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics*, 36:337–386.

Hoberg, G. and Phillips, G. (2010). Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis. *Review of Financial Studies*, 23(10):3773–3811.

Hoberg, G. and Phillips, G. (2016). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, 124(5):1423–1465.

Hong, H. and Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *Journal of Finance*, 58(1):313–351.

Hong, H. and Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance*, 54(6):2143–2184.

Huang, A. H., Zang, A., and Zheng, R. (2014). Evidence on the Information Content of Text in Analyst Reports. *Accounting Review*, 89(6):2151–2180.

Hugon, A. and Lin, A.-p. (2013). Analysts, Macroeconomic News, and the Benefit of Active In-House Economists. *Working paper*.

Hulten, C. R. (1978). Growth Accounting with Intermediate Inputs. *The Review of Economic Studies*, 45(3):511–518.

İmrohoroğlu, A. and Tüzel, Ş. (2014). Firm-Level Productivity, Risk, and Return. *Management Science*, 60(8):2073–2090.

Jaffe, A. B., Trajtenberg, M., and Fogarty, M. S. (2000). Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. *American Economic Review*, 90(2):215–218.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics*, 108(3):577–598.

Jannati, S., Korniotis, G., and Kumar, A. (2018). Big Fish in a Small Pond: The Economic Effects of Locally-Dominant Firms. *Working Paper*.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. C. (2004). Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance*, 59(3):1083–1124.

Kelly, B. T., Lustig, H. N., and Van Nieuwerburgh, S. (2013). Firm Volatility in Granular Networks. *Working Paper*, pages 1–54.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):665–712.

Korniotis, G. M. and Kumar, A. (2013). State-Level Business Cycles and Local Return Predictability. *Journal of Finance*, 68(3):1037–1096.

Kumar, A. (2010). Self-Selection and the Forecasting Abilities of Female Equity Analysts. *Journal of Accounting Research*, 48(2):393–435.

Levine, R. (1997). Financial Development and Economic Growth: Views and Agenda. *Journal of Economic Literature*, XXXV:688–726.

Lim, T. (2001). Rationality and Analysts' Forecast Bias. *Journal of Finance*, 56(1):369–385.

Malevergne, Y., Santa-Clara, P., and Sornette, D. (2009). Professor Zipf Goes to Wall Street. *NBER Working Papers*.

Malloy, C. J. (2005). The Geography of Equity Analysis. *Journal of Finance*, 60(2):719–755.

Matsumoto, D. A. (2002). Management's Incentive to Avoid Negative Earnings Surprises. *The Accounting Review*, 77(3):483–514.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *Journal of Finance*, 65(4):1555–1580.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55:703–708.

Ortiz-Molina, H. and Phillips, G. M. (2014). Real Asset Illiquidity and the Cost of Capital. *Journal of Financial and Quantitative Analysis*, 49(01):1–32.

Parsons, C. A., Sabbatucci, R., and Titman, S. (2016). Geographic Momentum. *Working Paper*.

Pastor, L. and Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111(3):642–685.

Richardson, S. a., Teoh, S. H., and Wysocki, P. D. (1999). Tracking Analysts' Forecasts over the Annual Earnings Horizon: Are Analysts' Forecasts Optimistic or Pessimistic? *Working Paper*, page 0.

Tappeiner, G., Hauser, C., and Walde, J. (2008). Regional knowledge spillovers: Fact or artifact? *Research Policy*, 37(5):861–874.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *RAND Journal of Economics*, 21:172–187.

Wallsten, S. J. (2001). An Empirical Test of Geographic Knowledge Spillovers Using Geographic Information Systems and Firm-Level Data. *Regional Science and Urban Economics*, 31:571–599.

Figure 1. Geographic Distribution of Dominant Firms

This figure shows the geographic distribution of dominant firms across the U.S. states. Dominant firms are the U.S. top-100 largest firms defined based on firms' prior year net sales. Firm information is from Compustat. The sample period is from 1995 to 2015.

Table 1. Summary Statistics

This table presents the summary statistics of the main variables used in the analysis. Panels A and B show the summary statistics for the dominant and non-dominant firms. Panel C reports the Pearson correlations, where ** represents significance at the 5% level. Dominant firms are the U.S. top-100 largest firms defined based on firms' prior year net sales. The first proxy for a firm's *Productivity Shocks* is the difference between the firm's and the average of other firms' productivity growth (Equation 2). The second measure of *Productivity Shocks* uses the estimated residual from Regression 4. *Market-to-Book Ratio* is the sum of market equity, short-term debt, and long-term debt, divided by total assets. *Loss* is a dummy that takes a value of 1 when operating income (dividend) is negative. *Size* is the natural logarithm of total assets. *Leverage* is the sum of short-term and long-term debts, divided by total assets. *Cash flows* show the cash flows from operating activities divided by the total assets. *State Income Tax* shows the state income taxes paid by a dominant firm at time t (Equation 18). $Number\ of\ Patents$ show the total number of patents a firm issues per year. $Citation-Weighted\ Patents$ is from Equation 9 and proxies for the value of patents each firm issues. The specific sources of each variable are reported in Table A1. The sample period is from 1995 to 2015.

Panel A: Dominant Firms						
Main Variables	Mean	25th pctl	Median	75th pctl	Std.	# of Obs.
Productivity Shocks (measure 1) (%)	0.000	-3.943	-0.243	4.235	12.330	2,100
Productivity Shocks (measure 2) (%)	-2.172	-8.004	-2.001	3.816	13.324	2,100
Market-to-Book Ratio	1.924	1.251	1.630	2.333	0.947	2,100
Loss	0.105	0.000	0.000	0.000	0.306	2,100
Size	9.722	9.327	9.972	10.256	0.629	2,100
Sales ($ Million)	19,302	13,904	20,737	25,023	5,965	2,100
Employees (in 1000)	76.094	43.950	74.517	117.000	36.146	2,100
Leverage	0.255	0.177	0.275	0.313	0.115	2,100
Cash Flows	0.104	0.082	0.106	0.118	0.045	2,100
State Income Tax ($ Million)	42.978	5.205	30.319	74.925	41.434	1,799
Number of Patents	147.258	0	10	129.5	410.296	1,600
Citation-Weighted Patents	325.487	0	19.0574	257.141	964.247	1,600
Panel B: Non-Dominant Firms						
Productivity Shocks (measure 1) (%)	0.000	-10.139	-0.600	9.222	44.412	55,333
Productivity Shocks (measure 2) (%)	0.170	-11.098	-0.347	10.228	43.769	55,333
Market-to-Book Ratio	2.034	1.065	1.465	2.259	2.072	55,333
Loss	0.368	0.000	0.000	1.000	0.482	55,333
Size	5.332	3.938	5.239	6.669	1.853	55,333
Sales ($ Million)	871	48	206	809	1,717	55,333
Employees (in 1000)	4.714	0.236	1.000	4.100	10.730	55,333
Leverage	0.215	0.010	0.162	0.337	0.235	55,333
Cash Flows	0.035	-0.004	0.069	0.126	0.167	55,333
State Income Tax ($ Million)	2.516	0.000	0.200	1.599	8.791	40,732
Number of Patents	3.913	0	0	1	27.205	41,277
Citation-Weighted Patents	9.350	0	0	2.0416	65.763	41,277

Panel C: Correlations			
	Non-Dominant Firms' Shocks (t)	Dominant Firms' Shocks ($t-1$)	Non-Dominant Firms' Shocks ($t-1$)
Non-Dominant Firms' Shocks (t)	**1**		
Dominant Firms' Shocks ($t-1$)	0.004**	**1**	
Non-Dominant Firms' Shocks ($t-1$)	-0.233**	0.002	**1**

Table 2. Geographic Spillover of Dominant Firms' Shocks
This table shows the propagation of dominant firms' productivity shocks to non-dominant firms in the same state. Specifically, this table tests the following Fama and Macbeth (1973) regression: $\textit{Non-Dominant Firm's Shocks}_{j,t+1} = \alpha_j + \beta_1 \ \textit{Dominant Firm's Shocks}_{i,t} + \beta X_{j,t} + \varepsilon_{j,t+1}$. Estimates in Panel A use Equation 3 to measure productivity shocks. Estimates in Panel B use $\varepsilon_{j,i,s,t}$ from Regression 4 to proxy for firm-specific productivity shocks. Columns 1 and 4 show the estimates with the sample of all non-dominant firms that are headquartered in the same state as the dominant firms. Columns 2 and 5 show the results for the sample of non-dominant firms that share the same industry and headquarter state with the dominant firms. Columns 3 and 6 show the results for the sample of non-dominant firms that are headquartered in the same state as the dominant firms but operate in a different industry. Firm data are from Compustat. GDP information is from the BEA. The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks (*t+1*)					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Dominant Firm's	**0.0049**	**0.0202**	**0.0033**	**0.0058**	**0.0348**	**0.0044**
Productivity Shocks (t)	**(2.46)**	**(2.02)**	**(2.26)**	**(4.67)**	**(2.55)**	**(6.47)**
Non-dominant Firm's	-0.1982	-0.1216	-0.2017	-0.1920	-0.2003	-0.1928
Productivity Shocks (t)	(-3.50)	(-2.94)	(-3.63)	(-10.97)	(-5.47)	(-11.58)
Cash Flows (t)	-0.0017	0.0183	-0.0032	-0.0818	-0.0882	-0.0821
	(-0.31)	(2.46)	(-0.61)	(-6.51)	(-1.82)	(-7.54)
Leverage (t)	0.0245	0.0386	0.0238	0.0203	0.0280	0.0199
	(6.83)	(5.05)	(6.25)	(2.30)	(2.09)	(2.13)
Dividend Yield (t)	-0.3125	-0.1124	-0.3239	-0.1667	-0.0400	-0.1751
	(-1.24)	(-1.73)	(-1.22)	(-1.60)	(-0.71)	(-1.63)
Market-to-Book (t)	0.0077	0.0262	0.0069	0.0252	0.0470	0.0237
	(2.13)	(2.70)	(1.92)	(2.12)	(2.69)	(1.85)
Loss (t)	0.0272	0.0757	0.0245	0.0712	0.0603	0.0723
	(2.55)	(5.82)	(2.29)	(7.27)	(2.25)	(7.16)
Size (t)	-0.0307	-0.0805	-0.0284	0.0422	0.0255	0.0434
	(-3.08)	(-5.49)	(-2.85)	(5.41)	(2.03)	(5.79)
Constant	-0.0170	-0.0275	-0.0161	-0.0416	-0.0300	-0.0424
	(-0.75)	(-1.71)	(-0.69)	(-7.44)	(-2.44)	(-6.83)
# of Obs.	251,918	16,150	235,768	251,219	16,116	235,103
Average R^2	0.11	0.11	0.11	0.08	0.13	0.08

Table 3. Dominant Firms and Out-of-Sector Non-Dominant Firms
This table reports evidence that the documented shock spillover in Table 2 is over and above intra-sector connections between dominant and local non-dominant firms. Specifically, Column 1 shows the estimates from a Fama and Macbeth (1973) regression where I exclude any pairs of dominant and non-dominant firms that have a positive similarity in their product markets. Column 2 shows the results after excluding dominant and non-dominant firms that, although not sharing a similar industry or product market, have *High IO* connections. Column 3 shows the estimates that exclude firm pairs that, although not sharing a similar industry or product market, have direct customer-supplier links. Column 4 excludes dominant firms that work in industries with more than 80% out-of-sector supplier-customer connections (i.e., service industries). *High IO* is a dummy variable equal to 1 if more than 5% of the total inputs of a non-dominant firm's industry are from a dominant firm's sector. Firm data are from Compustat. GDP information is from the BEA. TNIC data are from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). IO data are from the Benchmark Use Table available on the BEA. Firms' customer-supplier connections are from Cohen and Frazzini (2008). The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks (t+1)			
	(1)	(2)	(3)	(4)
Dominant Firm's Productivity Shocks (t)	**0.0035**	**0.0064**	**0.0036**	**0.0043**
	(2.65)	**(2.74)**	**(2.68)**	**(2.11)**
Non-Dominant Firm's Productivity Shocks (t)	-0.2035	-0.2068	-0.2032	-0.1977
	(-3.72)	(-3.39)	(-3.45)	(-3.94)
Cash Flows (t)	-0.0038	-0.0075	-0.0038	-0.0027
	(-0.75)	(-0.92)	(-0.75)	(-0.48)
Leverage (t)	0.0237	0.0229	0.0237	0.0236
	(6.20)	(5.44)	(6.22)	(6.47)
Dividend Yield (t)	-0.3262	-0.2394	-0.3264	-0.2843
	(-1.22)	(-1.21)	(-1.22)	(-1.21)
Market-to-Book (t)	0.0066	0.0069	0.0066	0.0079
	(1.94)	(2.17)	(1.92)	(2.25)
Loss (t)	0.0231	0.0186	0.0230	0.0232
	(2.16)	(1.43)	(2.15)	(2.18)
Size (t)	-0.0280	-0.0157	-0.0280	-0.0311
	(-2.85)	(-1.08)	(-2.86)	(-3.22)
Constant	-0.0158	-0.0137	-0.0158	-0.0151
	(-0.67)	(-0.58)	(-0.67)	(-0.69)
# of Obs.	232,523	12,0366	232,312	197,605
Average R^2	0.12	0.12	0.12	0.12

Table 4. Shock Spillovers Beyond Trade Links: Knowledge Externalities
This table shows the impact of dominant firms' knowledge externalities on the geographic spillover of shocks, beyond trade links. Column 1 shows the estimates for Regression 12, where *Contribution to Local Knowledge*$_t$ is the contribution of a dominant firms to the total patents issued in its headquarter state at time t (Equation 10). Column 2 shows the estimate results for Regression 13, where *Dollar Contribution to Local Knowledge* shows the dollar contribution of a dominant firm to the total value of patents issued in its headquarter state at time t (Equation 11). Column 3 shows the estimates for Regression 14, where *Similar Subclass*$_t$ is a dummy variable equal to 1, if at time t, a dominant and a local non-dominant firms have more than 20% similarity in the subclasses of their patents. Column 4 shows the estimate results with *Local Citations* as the main independent variable (Equation 15), where *Local Citations* shows the ratio of total citations a dominant firm receives from local non-dominant firms to the total citations received from all firms in the sample. The analysis of this table focuses on dominant and non-dominant pairs that are headquartered in the same state but operate in different industries. Firm data are from Compustat. Patent data are from Kogan et al. (2017). GDP information is from the BEA. The sample period is from 1995 to 2010. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

Dependent Variable: Non-Dominant Firm's Productivity Shocks (*t+1*)				
	(1)	(2)	(3)	(4)
Dominant Firm's Productivity Shocks (t)	-0.0024	-0.0023	-0.0799	0.0108
	(-2.47)	(-2.37)	(-1.75)	(1.72)
Dominant Firm's *Contribution to Local Knowledge* (t)	0.0018			
	(0.73)			
Contribution to Local Knowledge × Dominant Firm's Productivity Shocks (t)	**0.0063**			
	(4.62)			
Dominant Firm's *Dollar Contribution to Local Knowledge* (t)		0.0018		
		(0.71)		
Dollar Contribution to Local Knowledge× Dominant Firm's Productivity Shocks (t)		**0.0067**		
		(4.21)		
Similar Subclass (t)			-0.0068	
			(-0.18)	
Similar Subclass × Dominant Firm's Productivity Shocks (t)			**0.1005**	
			(2.24)	
Dominant Firm's Local Citations (t)				0.0024
				(0.28)
Local Citations × Dominant Firm's Productivity Shocks (t)				**0.0407**
				(1.84)
Firm Control	Yes	Yes	Yes	Yes
# of Obs.	178,253	178,253	12,413	179,211
Average R^2	0.15	0.15	0.20	0.15

Table 5. Shock Spillovers Beyond Trade Links: State Income Taxes

This table shows the impact of state income tax payments on the geographic spillover of shocks from dominant firms to out-of-sector non-dominant firms. Column 1 shows the estimation results for Regression 17, where $Income\ Tax\ Increase_t$ is a dummy variable equal to 1, if at time t a state has a positive $Income\ Tax\ Rate$ (Equation 16). Column 2 shows the estimates for Regression 19, where $State\ Tax_t$ shows the state income taxes paid by a dominant firm at time t (Equation 18). In Columns 3 and 4, I additionally adjust the state tax payments of dominant firms by the total amount of corporate income taxes, and the total income taxes generated in the dominant firms' states (Equations 20 and 21). Firm data are from Compustat. GDP information is from the BEA. Information on states' total income taxes is from the Federal Reserve Economic Data (FRED). The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates. Standard errors are clustered at the state and year levels in Column 1. Standard errors are adjusted using the Newey and West's (1987) method in Columns 2 to 4. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks (t+1)			
	(1)	(2)	(3)	(4)
Income Tax Increase (t)	**0.0375**			
	(1.75)			
Dominant Firm's Productivity Shocks (t)		0.0056	0.0047	0.0029
		(3.90)	(2.33)	(1.93)
Dominant Firm's State Tax (t)		-0.0009		
		(-1.43)		
State Tax × Dominant Firm's Productivity Shocks (t)		**0.0074**		
		(2.23)		
Dominant Firm's Contribution to Local Corporate Income Taxes (t)			0.0029	
			(1.36)	
Contribution to Local Corporate Income Taxes × Dominant Firm's Productivity Shocks (t)			**0.0130**	
			(2.06)	
Dominant Firm's Contribution to Local Income Taxes (t)				0.0014
				(0.42)
Contribution to Local Income Taxes × Dominant Firm's Productivity Shocks (t)				**0.0072**
				(2.59)
Firm Control	Yes	Yes	Yes	Yes
Year and State FEs	Yes			
# of Obs.	47,879	195,574	195,574	74,247
Adjusted, Average R^2	0.03	0.12	0.12	0.07

Table 6. Robustness Checks and Alternative Explanations

This table shows additional robustness checks for the main results. Column 1 shows the estimates that restrict the sample to dominant and non-dominant firms with the highest economic presence in their headquarter states. Column 2 shows the regression results that adjust shocks to common-local shocks (Equation 22). Column 3 restricts the sample to states with maximum four dominant firms. Column 4 shows the regression results that adjust shocks to common-industry shocks (Equation 23). Column 5 shows the estimates using TFP as a measure of firms' productivity (Equation 24). Column 6 shows the regression results with the weighted average of dominant firms' shocks as the main independent variable (Equation 25). Column 7 shows the estimates excluding states with a high agglomeration of dominant firms (i.e., CA, NY, TX, and IL). Column 8 excludes merger activities from the sample. Column 9 restricts the sample to periods before the 2008 financial crisis. Firm data are from Compustat. GDP information is from the BEA. Citation share data are from Bernile et al. (2016). TFP data are from İmrohoroğlu and Tüzel (2014). Information on firms' merger activities is from CRSP. The sample period is from 1995 to 2012; 1995 to 2015; 1995 to 2009; 1995 to 2015; and 1995 to 2007 in Columns 1; 2 to 4; 5; 6 to 8; and 9, respectively. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shock ($t+1$)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dominant Firm's Productivity Shocks (t)	**0.0069**	**0.0084**	**0.0203**	**0.0057**	**0.0033**		**0.0073**	**0.0048**	**0.0042**
	(3.18)	**(4.62)**	**(2.07)**	**(2.05)**	**(2.35)**		**(2.15)**	**(2.47)**	**(2.19)**
Weighted Average of Dominant Firm's Shocks (t)						**0.0324**			
						(2.29)			
Non-Dominant Firm's Productivity Shocks (t)	-0.1444	-0.1891	-0.1977	-0.1912	-0.2972	-0.1886	-0.1801	-0.2004	-0.2816
	(-2.48)	(-3.30)	(-9.80)	(-3.94)	(-5.52)	(-5.58)	(-3.71)	(-3.51)	(-5.10)
Cash Flows (t)	-0.0018	-0.0049	0.0109	-0.0059	-0.0259	0.0025	0.0004	-0.0016	-0.0067
	(-0.50)	(-0.85)	(1.60)	(-0.92)	(-6.38)	(0.77)	(0.11)	(-0.32)	(-1.13)
Leverage (t)	0.0401	0.0243	0.0081	0.0221	0.0281	0.0255	0.0317	0.0245	0.0226
	(5.26)	(5.63)	(0.79)	(4.58)	(7.33)	(6.89)	(5.16)	(6.88)	(4.49)
Dividends Yield (t)	-0.0281	-0.3275	-0.0189	-0.3606	-0.2402	-0.1293	-0.0656	-0.3133	-0.4987
	(-0.50)	(-1.23)	(-0.51)	(-1.23)	(-1.90)	(-1.40)	(-2.17)	(-1.24)	(-1.43)
Market-to-Book (t)	0.0104	0.0062	0.0098	0.0018	0.0162	0.0098	0.0102	0.0075	0.0033
	(1.55)	(2.40)	(2.69)	(0.52)	(3.81)	(1.62)	(1.31)	(2.11)	(1.63)
Loss (t)	0.0185	0.0244	0.0366	0.0219	0.0111	0.0353	0.0394	0.0270	0.0343
	(1.94)	(2.35)	(1.65)	(2.16)	(0.48)	(3.26)	(2.29)	(2.43)	(2.64)
Size (t)	-0.0516	-0.0193	-0.0643	-0.0148	-0.0562	-0.0430	-0.0441	-0.0310	-0.0156
	(-4.23)	(-1.62)	(-2.92)	(-1.71)	(-2.43)	(-3.55)	(-2.91)	(-3.04)	(-1.06)
Constant	0.0061	-0.0161	-0.0152	-0.0187	-0.0013	-0.0185	-0.0077	-0.0166	-0.0323
	(0.35)	(-0.78)	(-0.53)	(-0.74)	(-0.05)	(-0.90)	(-0.41)	(-0.73)	(-1.05)
# of Obs.	80,061	235,767	5,285	235768	127906	42,417	67,613	249,851	167,481
Average R^2	0.13	0.12	0.14	0.11	0.14	0.09	0.08	0.12	0.16

Table 7. Dominant Firms' Shock Spillovers and Asset Prices
This table examines the market understanding of the effects that dominant firms' productivity shocks have on local non-dominant firms. Each year, I sort the U.S. states into deciles based on the weighted average of dominant firms' productivity shocks (Equation 25), where the tenth (first) decile contains states with the most positive (negative) weighted average of dominant firms' shocks. Based on the information of the prior year, I create a zero-cost portfolio that goes long on non-dominant firms in the states of the tenth decile, and short on non-dominant firms headquartered in the states of the first decile. Following Fama and French (1993), portfolios' return are calculated from July of year t to June of $t+1$, and are rebalanced in June of $t+1$. Panel A shows the average of monthly excess return for each portfolio along with the portfolio's standard deviation (Std.), Sharpe ratio, percent shares of the market capital, and percent shares of the U.S. states. Panel B (Panel C) shows the abnormal return of the equally-weighted (value-weighted) long-short portfolio. The sample used in Panels A, B, and C includes all non-dominant firms that share the same headquarter state with the dominant firms. Panel D (Panel E) repeats the same analysis in Panel B, but excludes (only includes) intra-sector non-dominant firms. The explanatory variables in Panels B, C, D, and E include the Fama and French's (1993) three factors, the Carhart's (1997) momentum factor, and Pastor and Stambaugh's (2003) liquidity factor. Monthly returns are from CRSP. The sample period is from July 1996 to December 2015. The t-statistics are shown below the coefficient estimates are based on standard errors that are clustered at the year and month levels. Coefficients of interest are shown in bold.

Panel A: All Local Non-Dominant Firms					
Decile	Average of Monthly Excess Return (%)	Std. (%)	Sharpe Ratio (%)	Market Share (%)	State (%)
Long-Short	**0.44**	**2.68**	**16.37**	**5.28**	**18.78**
1 (Short)	0.79	6.88	11.53	2.63	7.51
2	0.79	6.91	11.45	2.37	10.74
3	1.09	6.50	16.74	1.21	10.08
4	0.99	6.91	14.31	0.99	9.70
5	1.09	6.85	15.85	1.22	10.47
6	0.71	7.38	9.59	0.80	8.87
7	0.99	6.51	15.23	1.26	8.91
8	0.55	6.92	8.00	1.70	10.39
9	1.03	7.04	14.59	1.71	10.34
10 (Long)	1.23	6.68	18.44	2.64	11.27
Panel B: All Local Non-Dominant Firms– Equally-Weighted Portfolios					
	CAPM	Three Factor	Four Factor	Five Factor	
Long-Short Alpha (× 100)	**0.425**	**0.414**	**0.320**	**0.373**	
	(2.48)	**(2.46)**	**(1.92)**	**(2.17)**	
Panel C: All Local Non-Dominant Firms– Value-Weighted Portfolios					
	CAPM	Three Factor	Four Factor	Five Factor	
Long-Short Alpha (× 100)	**0.719**	**0.689**	**0.595**	**0.605**	
	(2.30)	**(2.37)**	**(2.11)**	**(2.04)**	
Panel D: Out-of-Sector Non-Dominant Firms– Equally-Weighted Portfolios					
	CAPM	Three Factor	Four Factor	Five Factor	
Long-Short Alpha (× 100)	**0.385**	**0.379**	**0.298**	**0.347**	
	(2.04)	**(2.08)**	**(1.63)**	**(1.83)**	
Panel E: Intra-Sector Non-Dominant Firms– Equally-Weighted Portfolios					
	CAPM	Three Factor	Four Factor	Five Factor	
Long-Short Alpha (× 100)	**0.465**	**0.476**	**0.340**	**0.394**	
	(1.79)	**(1.83)**	**(1.33)**	**(1.48)**	
Number of Months	234	234	234	234	

Table 8. Dominant Firms' Shock Spillovers and Asset Prices: Double-Sorted Portfolios

This table performs a double-sorted analysis to investigate the slow diffusion of information, contained in dominant firms' shocks. Based on the monthly estimates of β_2 (from Regression 27), I sort non-dominant firms in two groups: (1) *High-beta* non-dominant firms, as those with an above-the-median β_2, and (2) *Low-beta* non-dominant firms, as those with a below-the-median β_2. Next, I independently sort non-dominant firms on the sensitivity of their monthly returns to those of local dominant firms (i.e., β_2) and the weighted average of dominant firms' shocks in their headquarter states (similar to Table 7). Following Fama and French (1993), portfolios' return are calculated from July of year t to June of $t+1$, and are rebalanced in June of $t+1$. Panel A shows the average of monthly excess return for each portfolio along with the portfolio's standard deviation (Std.), Sharpe ratio, and percent shares of the market capital. Panel B shows the abnormal return of the equally-weighted long-short portfolio. The sample used in Panels A and B includes all non-dominant firms that share the same headquarter state as dominant firms. Panel C (Panel D) repeats the same analysis in Panel B, but excludes (only includes) intra-sector non-dominant firms. The explanatory variables in Panels B, C, and D include the Fama and French's (1993) three factors, the Carhart's (1997) momentum factor, and Pastor and Stambaugh's (2003) liquidity factor. Monthly returns are from CRSP. The sample period is from July 1996 to December 2015. The t-statistics are shown below the coefficient estimates are based on standard errors that are clustered at the year and month levels. Coefficients of interest are shown in bold.

	Low-Beta Non-Dominant Firms				High-Beta Non-Dominant Firms			
Panel A: All Local Non-Dominant Firms								
Decile	Average of Monthly Excess Return (%)	Std. (%)	Sharpe Ratio (%)	Market Share (%)	Average of Monthly Excess Return (%)	Std. (%)	Sharpe Ratio (%)	Market Share (%)
Long-Short	**0.11**	**2.892**	**3.88**	**2.07**	**0.74**	**3.729**	**19.78**	**3.17**
1 (Short)	0.91	6.84	13.25	1.05	0.65	6.88	9.45	1.57
2	0.75	6.82	11.01	0.94	0.84	6.50	12.95	1.41
3	0.96	7.56	12.66	0.55	1.06	6.24	16.99	0.67
4	0.92	7.43	12.44	0.49	1.02	6.77	15.03	0.49
5	0.94	7.27	12.87	0.50	1.19	7.02	16.96	0.67
6	0.70	7.54	9.27	0.40	0.88	7.12	12.42	0.42
7	0.75	7.95	9.40	0.63	1.15	6.94	16.54	0.63
8	0.48	6.99	6.85	0.66	0.64	6.87	9.35	1.03
9	0.95	7.54	12.60	0.80	1.08	6.83	15.84	0.90
10 (Long)	1.02	7.25	14.04	1.02	1.39	7.08	19.62	1.61
Panel B: All Local Non-Dominant Firms– Equally-Weighted Portfolios								
	CAPM	Three Factor	Four Factor	Five Factor	CAPM	Three Factor	Four Factor	Five Factor
Long-Short Alpha ($\times$ 100)	**0.0688**	**0.0766**	**0.0675**	**0.145**	**0.743**	**0.718**	**0.579**	**0.597**
	(0.37)	**(0.40)**	**(0.30)**	**(0.67)**	**(3.05)**	**(3.10)**	**(2.57)**	**(2.57)**
Panel C: Out-of-Sector Non-Dominant Firms– Equally-Weighted Portfolios								
	CAPM	Three Factor	Four Factor	Five Factor	CAPM	Three Factor	Four Factor	Five Factor
Long-Short Alpha ($\times$ 100)	**0.0968**	**0.101**	**0.0793**	**0.168**	**0.654**	**0.635**	**0.516**	**0.524**
	(0.45)	**(0.47)**	**(0.33)**	**(0.69)**	**(2.64)**	**(2.72)**	**(2.29)**	**(2.25)**
Panel D: Intra-sector Non-Dominant Firms– Equally-Weighted Portfolios								
	CAPM	Three Factor	Four Factor	Five Factor	CAPM	Three Factor	Four Factor	Five Factor
Long-Short Alpha ($\times$ 100)	**0.112**	**0.155**	**0.137**	**0.206**	**0.744**	**0.743**	**0.571**	**0.606**
	(0.35)	**(0.49)**	**(0.38)**	**(0.59)**	**(1.98)**	**(2.01)**	**(1.55)**	**(1.54)**
Number of Months	234	234	234	234	234	234	234	234

Table 9. Dominant Firms' Shock Spillovers and Analysts' Behavior
This table examines whether equity analysts incorporate the information contained in shocks to dominant firms, when they issue earnings forecasts for local non-dominant firms. Columns 1 to 3, and 7 to 9 report the estimation results for Regression 28. Columns 4 to 6, and 10 to 12 reports the estimation results for Regression 29. Panel A restricts the sample to dominant and non-dominant firms that share the same industry and headquarter state. Panel B restricts the sample to dominant and non-dominant firms that share the same headquarter state, but operate in different sectors. Stock information is from CRSP and Compustat. GDP information is from the BEA. Analysts' earnings forecasts are from IBES. All-star information is from Huang et al. (2014). Analyst location is from Antoniou et al. (2016). The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Panel A: Intra-Sector Non-Dominant Firms						Panel B: Out-of-Sector Non-Dominant Firms					
	Forecast Error			Accuracy			Forecast Error			Accuracy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dominant Firm's Productivity Shocks	**0.0234**			**-0.0040**			**-0.0008**			**0.0013**		
	(4.26)			**(-1.22)**			**(-0.20)**			**(0.33)**		
Dominant Firm's Positive Productivity Shocks		**0.0146**			**0.0064**			**-0.0014**			**0.0024**	
		(2.94)			**(1.12)**			**(-0.39)**			**(0.45)**	
Dominant Firm's Negative Productivity Shocks			**0.0067**			**-0.0131**			**0.0058**			**0.0019**
			(0.98)			**(-3.59)**			**(1.23)**			**(0.33)**
Brokerage Size	0.0023	-0.0035	0.0066	-0.0022	0.0038	-0.0053	-0.0167	-0.0212	-0.0142	-0.0088	-0.0123	-0.0071
	(0.27)	(-0.36)	(0.64)	(-0.21)	(0.28)	(-0.52)	(-2.10)	(-2.16)	(-1.78)	(-0.43)	(-0.49)	(-0.43)
Both-cover	-0.0002	0.0523	-0.0268	-0.0033	-0.0235	0.0081	-0.0249	-0.0128	-0.0266	0.0642	0.1881	0.0211
	(-0.01)	(1.14)	(-0.90)	(-0.10)	(-0.89)	(0.11)	(-0.37)	(-0.19)	(-0.33)	(0.99)	(3.90)	(0.26)
All-star	0.0871	0.1048	0.0714	0.0850	0.0900	0.0777	0.0173	0.0095	0.0273	0.0681	0.0686	0.0675
	(1.59)	(1.54)	(1.57)	(1.99)	(2.01)	(1.96)	(0.91)	(0.70)	(1.05)	(2.85)	(2.69)	(3.25)
Local Analyst	0.0346	0.0206	0.0435	0.1052	0.1311	0.0867	-0.0282	-0.0102	-0.0366	-0.0539	-0.0350	-0.0529
	(1.20)	(0.56)	(1.67)	(4.05)	(3.36)	(4.67)	(-1.06)	(-0.39)	(-1.36)	(-4.96)	(-2.49)	(-3.69)
Experience	-0.0436	-0.0222	-0.0588	-0.0282	-0.0216	-0.0323	-0.0070	-0.0104	-0.0117	-0.0313	-0.0352	-0.0319
	(-1.37)	(-0.92)	(-1.68)	(-2.21)	(-1.44)	(-1.88)	(-0.45)	(-0.52)	(-0.77)	(-1.46)	(-1.31)	(-1.66)
Forecast Age	0.0007	0.0007	0.0007	0.0009	0.0009	0.0009	0.0010	0.0010	0.0010	0.0008	0.0008	0.0007
	(5.19)	(5.99)	(4.88)	(10.25)	(10.30)	(9.90)	(9.50)	(8.18)	(10.25)	(4.14)	(4.05)	(4.14)
Constant	0.4823	0.4284	0.5320	1.5791	1.5773	1.5909	0.6680	0.5876	0.7335	1.7945	1.7248	1.8557
	(4.15)	(3.81)	(4.18)	(11.77)	(11.32)	(12.12)	(10.96)	(13.06)	(10.79)	(8.43)	(9.07)	(8.17)
Firm Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	272,557	121,685	150,872	272,557	121,685	150,872	340,412	164,437	175,975	340,412	164,437	175,975
Average R^2	0.045	0.046	0.049	0.2577	0.2495	0.2684	0.059	0.057	0.062	0.239	0.232	0.250

Appendices

to accompany

Geographic Spillover of Dominant Firms' Shocks

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

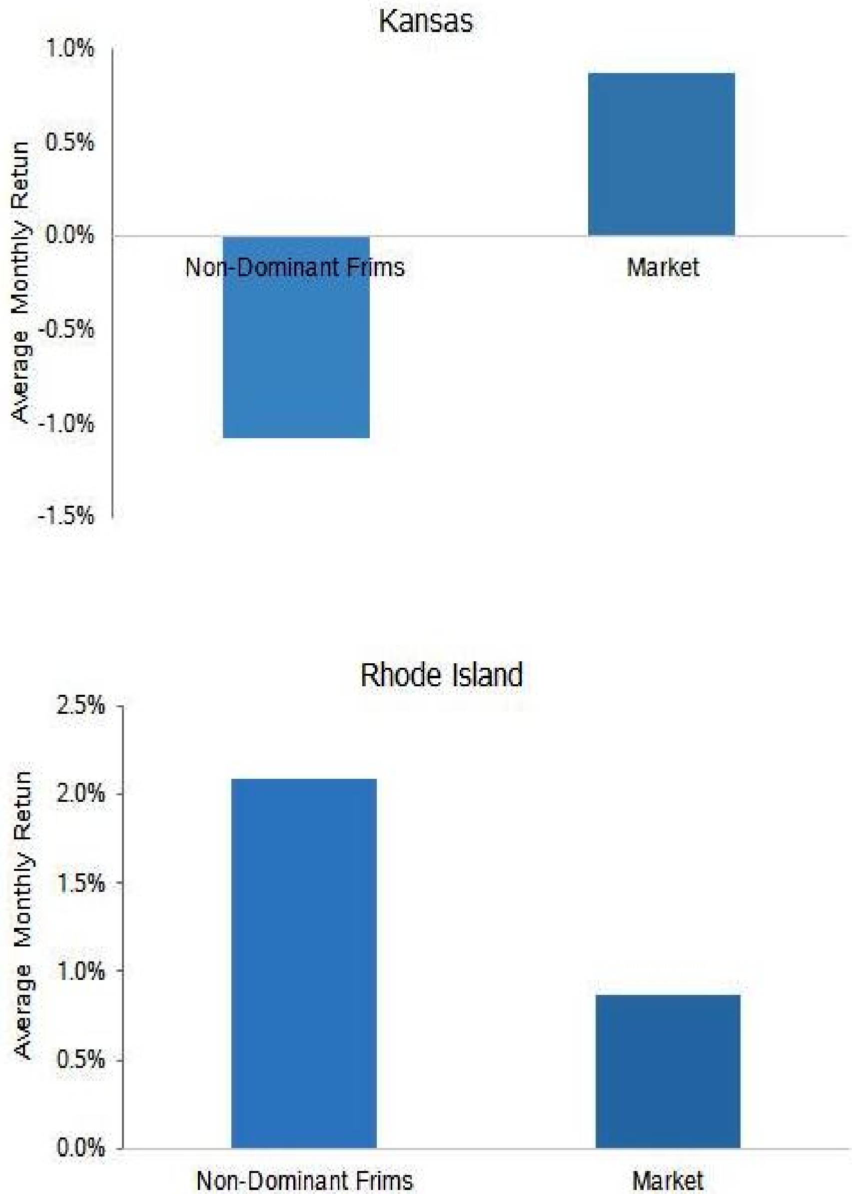

Figure A1. Dominant Firms' Shock Spillovers to Out-of-Sector Firms: An Example
This figure shows the geographic spillover of dominant firms' shocks in a random year (2005) in two random states: Kansas and Rhode Island. In 2005, a Kansas dominant firm, Sprint, experienced a negative productivity shock followed by the unsuccessful merger experience with Nextel. In the same year, a Rhode Island dominant firm, Textron, experienced a positive shock followed by a considerable shift in its product demands. This figure compares the non-dominant firms' weighted-average monthly returns with the market's returns over 2005 and 2006. The sample of non-dominant firms includes those that are headquartered in the two states but do not share the same industry with the local dominant firms. Specifically, the non-dominant firms in Kansas (Rhode Island) are outside of the communication (aircraft) industry. The weighted average of monthly returns is calculated using firms' market capitalization. Firm data are from Compustat and CRSP. Market's monthly returns are from K. French's website.

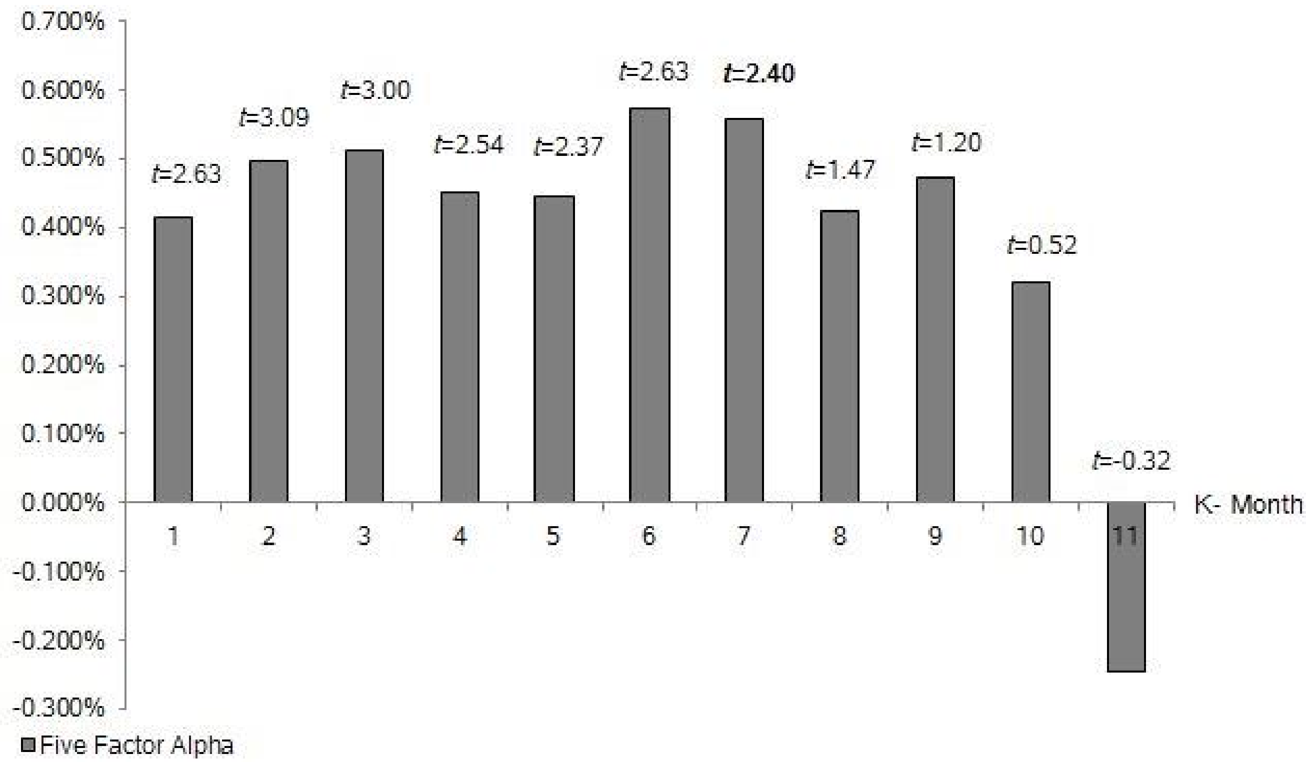

Figure A2. Delayed Portfolio Formation
This figure shows the performance (i.e., alpha) of the long-short portfolio (in Section 4.1) K month after forming the portfolio. I sort the U.S. states into deciles based on the weighted average of dominant firms' productivity shocks (Equation 25). Based on the information of the prior year, I create a zero-cost portfolio that goes long on non-dominant firms in the states of the tenth decile and goes short on non-dominant firms headquartered in the states of the first decile. The portfolios are rebalanced annually and are equally weighted. Performance is based on the five-factor model that includes the Fama and French (1993) three-factor, the Carhart (1997) momentum factor, and Pastor and Stambaugh (2003) liquidity factor. Monthly returns are from CRSP. The sample period is from July 1996 to December 2015. The t-statistics are shown above the alpha bars and are based on standard errors that are clustered at the year and month levels.

Table A1. Definition and Sources of Main Variables
This table defines the main variables used in the empirical analyses. The main data sources are (1) Center for Research on Security Prices (CRSP), (2) Annual CRSP-Compustat Merged (CCM), (3) Institutional Brokers Estimate System from Thomson Financial (IBES), and (4) Bureau of Economic Analysis (BEA).

Variables Name	Description	Source
	Firm Variables	
Dominant Firm Dummy	Set to 1, if a firm is among the U.S. top-100 largest firms	CCM
Productivity	*Sales/Employees*	CCM
Productivity Growth	Annual log change of productivity	CCM
Productivity Shocks	The difference between the firm's and the average of other firms' productivity growth	CCM
Number of Employees	Total number of employees	CCM
Sales	Net sales of a firm	CCM
Cash Flows	Cash flows from operating activities, divided by total assets	CCM
Leverage	Sum of short-term and long-term debt, divided by total asset	CCM
Dividend Yield	Dividend, divided by shareholders' equities	CCM
Market-to-Book Ratio	Sum of market equity, short term and long term debt, divided by total asset	CCM
Loss Dummy	Set to 1 if operating income is negative, 0 otherwise	CCM
Size	Natural logarithm of total assets	CCM
Earnings	Operating income after depreciation, divided by total asset	CCM
Industry Category	Fama-French 48 industry portfolios	K. French's Website
High IO Dummy	Set to 1, if a non-dominant firm's industry receives more than 5% of its total inputs from a dominant firm's sector	BEA
Number of Patents	Total number of patents issued by a firm	Kogan et al. 2017
State Tax	(Total Income Tax/Total Paid Tax)$\times$Income State Tax	CCM
Market Capitalization	Price $\times$ total number of shares outstanding	CRSP
	Equity Analyst Variables	
Forecast Error	(Analyst Forecast - Actual Earnings)/Price, where Price is the stock price two days before the forecast date	IBES, CRSP
Accuracy	Absolute value of forecast error	IBES, CRSP
All-Star Dummy	Set to 1 if an analyst is ranked among II All Americans list	Huang et al. 2014
Both-Cover Dummy	Set to 1 if an analyst covers a dominant and local non-dominant firm	IBES
Experience Dummy	Set to 1 if an analyst has more than 3 years of presence in the sample, and 0 otherwise	IBES
Local Analyst Dummy	Set to 1 if an analyst's brokerage is located in the same state as the firm that analyst covers	Antoniou et al. 2016

Table A2. Productivity Shocks: Examples
This table compares the estimated firm-specific shocks and the actual event that happened to a (random) dominant firm in a (random) year and state. Dominant firms are the top-100 largest firms in the economy, where size is the firm's prior year net sales. Dominant firm's shocks are the firm-specific component of the total productivity growth rate of the firm (Equation 2). Firm data are from Compustat. GDP information is from the BEA. Information about firm-specific events are from firms' 10-K and 8-K filings, available on the SEC.

HQ State	Dominant Firm	Year	Event	Estimated Productivity Shock
WI	Rockwell Automation	1996	Sales in 1996 were up 14% led by significant increases in the Automation, Semiconductor Systems and Automotive Light Vehicle Systems businesses	8.4%
TN	HCA Health-care	1999	Hospital Exec. imprisoned following a fraud case. Company was also facing many challenges, including a growing number of uninsured, reimbursement pressures.	-10.07%
RI	Textron Inc.	2002	As a result of restructuring program initiated in 2000, Textron reduced its workforce by approximately 8,100 employees representing more than 16% of its workforce.	-12.1%
RI	Textron Inc.	2005	Cessna received 52 Citation jet orders, worth more than $500 million and Bell received 35 helicopter orders, worth more than $100 million at the National Business Aviation Association (NBAA) convention.	13.8%
NY	Colgate-Palmolive	2015	Delay in achieving expected benefits from the 2012 "Restructuring Program."	-6.2%

Table A3. Economic Significance of Dominant Firms' Shock Spillovers

This table shows the effects of a non-dominant firm's productivity shocks on its earnings, sales, and cash flows. Specifically, this table tests the following regression: $\textit{Non-Dominant Firm's Earnings}_t = \alpha + \beta_1 \textit{ Non-Dominant Firm's Shocks}_t + \beta X_{t-1} + \varepsilon_t$. Column 1 shows the Fama and Macbeth (1973) regression on the effects of a non-dominant firm's shocks on its earnings. Columns 2 and 3 repeat the above regression, using the non-dominant firm's sales or cash flows as the dependent variable. Firm data are from Compustat. GDP information is from the BEA. The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's		
	Earnings (t)	Sales(t)	Cash Flows (t)
	(1)	(2)	(3)
Productivity Shocks (t)	**0.0152**	**0.0368**	**0.0266**
	(5.08)	**(2.19)**	**(2.33)**
Earnings (*t-1*)	0.3600	-0.1198	0.3467
	(11.99)	(-4.96)	(15.32)
Leverage (*t-1*)	0.0192	-0.0528	0.0082
	(2.33)	(-2.95)	(1.09)
Dividend Yield (*t-1*)	-0.0085	0.3100	-0.0039
	(-3.50)	(5.35)	(-1.87)
Market-to-Book (*t-1*)	0.0236	0.0373	0.0091
	(4.54)	(7.09)	(0.93)
Loss (*t-1*)	-0.0364	-0.0855	-0.0204
	(-1.80)	(-6.10)	(-1.06)
Size (*t-1*)	0.0302	0.735	0.0271
	(4.45)	(6.05)	(3.32)
Constant	0.0241	-0.0015	0.0212
	(2.17)	(-0.16)	(1.93)
# of Obs.	47,879	47,879	47,879
Average R^2	0.48	0.51	0.41

Table A4. Geographic Spillover of Dominant Firms' Shocks: Extended Sample
This table repeats the same analysis of Table 2, using an extended sample. In particular, I extend the sample from 1995 to 2015 (in the baseline analysis) to 1988 to 2015 in Columns 1 to 3. I extend the sample back to 1963 in Columns 4 to 6. Firm data are from Compustat. GDP information is from the BEA. The sample used in Columns 1 and 4 are dominant and non-dominant firms that are headquartered in the same state. Columns 2 and 5 restrict the sample to dominant and non-dominant firms that share the same headquarter state and industry. Columns 3 and 6 include dominant and non-dominant firms that are headquartered in the same state but operate in different industries. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks ($t+1$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Dominant Firm's Productivity Shocks (t)	**0.0052**	**0.0307**	**0.0037**	**0.0043**	**0.0151**	**0.0035**
	(3.64)	**(3.82)**	**(2.44)**	**(4.43)**	**(2.25)**	**(3.09)**
Non-Dominant Firm's Productivity Shocks (t)	-0.1749	-0.1113	-0.1751	-0.1894	-0.1443	-0.1903
	(-4.22)	(-3.18)	(-4.25)	(-8.21)	(-5.54)	(-8.30)
Leverage (t)	0.0141	0.0243	0.0136	0.0300	0.0283	0.0298
	(2.54)	(3.16)	(2.44)	(2.89)	(1.99)	(2.86)
Dividend Yield (t)	-0.1654	-0.0985	-0.1706	-0.3114	-0.6559	-0.3119
	(-1.50)	(-1.63)	(-1.47)	(-1.15)	(-1.12)	(-1.13)
Market-to-Book (t)	0.0006	0.0175	-0.0004	-0.0004	-0.0059	0.0002
	(0.11)	(2.98)	(-0.06)	(-0.05)	(-0.31)	(0.03)
Loss (t)	0.0337	0.0598	0.0317	0.0535	-0.0096	0.0542
	(3.63)	(3.05)	(3.38)	(1.77)	(-0.18)	(1.75)
Size (t)	-0.0157	-0.0144	-0.0154	0.0094	0.0315	0.0084
	(-1.81)	(-0.66)	(-1.80)	(0.77)	(0.96)	(0.71)
Cash Flow (t)	-0.0170	0.0350	-0.0224			
	(-0.78)	(1.18)	(-1.01)			
Constant	-0.0155	-0.0209	-0.0150	-0.0070	-0.0343	-0.0071
	(-1.42)	(-2.50)	(-1.31)	(-0.34)	(-1.02)	(-0.34)
# of Obs.	336,850	19,957	316,893	545,522	29,988	515,534
Average R^2	0.09	0.09	0.09	0.08	0.09	0.08

Table A5. Dynamic Effects of Dominant Firms' State Income Taxes

This table shows the dynamic impact of dominant firms' state income tax payments on the geographic spillover of productivity shocks. Specifically, this table repeats the same analysis as in Column 2 of Table 5, using the time-lagged state income taxes of dominant firms (i.e., $State\ Tax_{t-1}$, and $State\ Tax_{t-2}$). Firm data are from Compustat. GDP information is from the BEA. The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates are based on standard errors that are adjusted using the Newey and West's (1987) method. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks (*t+1*)		
	(1)	(2)	(3)
Dominant Firm's Productivity Shocks (t)	0.0056 (3.90)	0.0064 (4.88)	0.0056 (4.52)
State Tax (t)	-0.0009 (-1.43)		
State Tax (t) × Dominant Firm's Productivity Shocks (t)	**0.0074** **(2.23)**		
State Tax (*t-1*)		-0.0009 (-1.06)	
State Tax (*t-1*) × Dominant Firm's Productivity Shocks (t)		**0.0086** **(2.28)**	
State Tax (*t-2*)			-0.0028 (-2.45)
State Tax (*t-2*) × Dominant Firm's Productivity Shocks (t)			**0.0116** **(3.15)**
Firm Controls	Yes	Yes	Yes
# of Obs.	195,574	195,574	195,574
Average R^2	0.12	0.12	0.12

Table A6. Alternative Measure of Geographic Proximity

This table examines the propagation of productivity shocks, using MSA to identify the geographic networks between dominant and non-dominant firms. Column 1 uses the sample of dominant and non-dominant firms that are headquartered in the same MSA. Column 2 restricts the sample to dominant and non-dominant firms that are headquartered in the same MSA and operate in the same sector. Columns 3 restricts the sample to dominant and non-dominant firms that are located in the same MSA, but operate in different industries. Firm data are from Compustat. GDP and MSA data are from the BEA. The sample period is from 1995 to 2015. All of the continuous variables are standardized to have a mean equal to 0 and a standard deviation equal to 1. The t-statistics are reported in the parentheses below the coefficient estimates. Coefficients of interest are shown in bold.

	Dependent Variable: Non-Dominant Firm's Productivity Shocks (t+1)		
	(1)	(2)	(3)
Dominant Firm's Productivity Shocks (t)	**0.0143**	**0.0327**	**0.0141**
	(2.28)	**(1.71)**	**(2.15)**
Firm Control	Yes	Yes	Yes
# of Obs.	30,970	2,418	28,552
Average R^2	0.31	0.19	0.31
Sample	All firms in the same MSA	Firms in the same MSA and same industry	Firms in the same MSA and different industries

B Dominant Firms and Local Business Cycles

In this appendix, I study whether productivity shocks to dominant firms explain the GDP growth of their headquarter states. To this end, each year, I compute the productivity shocks to dominant firms using the method explained in Section 2.2.1. Subsequently, for each state, I calculate the weighted average of dominant firms' shocks as

$$\Gamma_{s,t} = \sum_{j=1}^{K} \frac{Sales_{j,t-1}}{GDP_{s,t-1}} \times Productivity\ Shocks_{j,t}, \tag{B1}$$

where K shows the total number of dominant firms in state s, at time t. Next, I study the effect of dominant firms' shocks on the GDP growth of their headquarter states, using the following time-series regression:

$$logGDP_{s,t} - logGDP_{s,t-1} = \alpha + \beta_1 \Gamma_{s,t} + \beta_2 \Gamma_{s,t-1} + \varepsilon_{s,t}. \tag{B2}$$

From the above regression, I am interested in the estimated R^2, which captures the economic power of $\Gamma_{s,t}$ and $\Gamma_{s,t-1}$ in explaining the state's GDP growth. Column 4 of Table B1 shows the estimated R^2 for each state (that has a dominant firm). As shown, the predictive power of dominant firms in explaining the state's economic growth is large and significant. For example, shocks to the only dominant firm in Nebraska (Union Pacific Railroad) explain more than 40% of the state's business cycle. This effect is more than 80% in Idaho. Together, this analysis shows that productivity shocks to dominant firms have substantial economic effects on the local business cycles.

Table B1. Dominant Firms and Local Business Cycles
This table shows the effects of dominant firms' productivity shocks on the economic growth of their headquarter states. Specifically, Column 2 shows the total number of dominant firms in each state. Column 3 shows the ratio of dominant firms to the total number of firms headquartered in the state. Column 4 reports the estimated R^2 for Regression B1. Firm data are from Compustat. State GDP information is from the BEA. The sample period is from 1995 to 2015.

(1) State	(2) # of Dominant Firms	(3) $\frac{\#\ of\ Dominant\ Firms}{Total\ \#\ of Firms}$ (%)	(4) R^2 (%)
Arkansas	3	10.0	14.0
Arizona	1	0.8	24.0
California	23	1.5	9.1
Colorado	3	1.4	63.8
Connecticut	2	1.2	17.2
Delaware	1	4.5	8.1
Florida	6	1.4	35.1
Georgia	9	4.3	35.4
Idaho	2	10.0	85.0
Illinois	25	8.7	3.7
Indiana	2	2.6	18.6
Kansas	1	5.1	32.2
Louisiana	2	9.7	0.9
Massachusetts	7	1.5	10.9
Maryland	2	1.4	30.6
Michigan	14	10.7	30.8
Minnesota	7	3.4	23.5
Missouri	7	6.5	3.3
North Carolina	4	2.4	24.7
Nebraska	1	3.7	43.7
New Jersey	13	3.4	7.9
New York	23	3.8	10.9
Ohio	8	3.4	3.0
Pennsylvania	6	2.0	29.0
Rhode Island	2	8.7	14.7
South Dakota	1	14.3	26.4
Tennessee	6	5.2	18.1
Texas	24	3.6	22.6
Utah	1	1.3	52.4
Virginia	8	3.4	34.1
Washington	8	5.2	1.1
Wisconsin	5	4.7	13.1