Idiosyncratic Shocks, Geographic Spillovers, and Asset Prices*

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Abstract – This paper shows that productivity shocks to the top 100 U.S. companies (as identified in Gabaix (2011)) 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 the cascade effect. However, these geographic spillovers are not only restricted to firms' explicit interactions. State income tax payments is another dominant channel through which the shocks propagate. Market participants, including equity analysts, do not fully incorporate the geographic information contained in shocks to top 100 firms. Consequently, a trading strategy that exploits the slow diffusion of information generates an annual risk-adjusted return of 7.5%.

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

JEL Classification: G02, G14, G24.

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1 Introduction

The U.S. economy consists of more than 5 million firms. Among these firms, a small number of companies are extremely large. These firms have a substantial effect on the national economy. In particular, Gabaix (2011) shows that productivity shocks to the 100 largest U.S. firms explain one-third of the U.S. business cycle. Despite its importance, the economic impact of the largest U.S. firms on other firms has not been thoroughly examined.[1]

In this study, motivated by the evidence in Gabaix (2011), I examine whether firm-specific shocks to the 100 largest U.S. firms (hereafter, dominant firms) contain relevant information for other firms.[2] Specifically, I examine whether productivity shocks to dominant firms affect other firms in the local economy. I also identify the economic mechanism through which shocks to these largest firms aggregate, and potentially affect the aggregate U.S. economy.

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. So far, the literature has mainly focused on the former type of connections.[3] While intra-sector links are economically important, firms can also affect each other even in the absence of direct economic connections (Dougal et al. (2015); Parsons et al. (2016)). In particular, the geographic network of very large and dominant firms and other firms can generate economic interactions beyond direct intra-sector linkages.

Further, dominant firms can have a considerable impact on their local economies.[4] This local impact can occur, for instance, via their state income tax payments, new job opportunities, charitable donations, or through their impact on local entrepreneurial activities. Consequently, a higher level of productivity shocks to dominant firms can lead to greater 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 direct connections among dominant firms and other neighboring firms.

[1]Anecdotal evidence highlights the potential influence of large companies on other firms. For example, the recent financial crisis demonstrated the significance of networks between large firms and other businesses (Billio et al. (2012); Hautsch et al. (2014)). As Acemoglu et al. (2012) argue, the government support provided to many of these firms during the crisis was not only because they were "too big to fail," but mainly due to their interconnections with other companies.

[2]Results are not sensitive to this cutoff. Specifically, increasing (decreasing) the sample of dominant firms to the 150 (50) largest firms in the U.S. results in consistent outcome.

[3]For example, see Cohen and Frazzini (2008); Acemoglu et al. (2012); Kelly et al. (2013); Foerster et al. (2011); and Wu (2016)).

[4]In Figure 1, I illustrate different mechanisms, and provide illustrative examples in Appendix B.1.

In particular, I expect that firm-specific productivity shocks to dominant firms would create future shocks to other local non-dominant firms. My key conjecture is that shocks to largest firms in the economy will spread geographically. To test this hypothesis, I identify local non-dominant firms as those that are headquartered in the same state as the dominant firms. Further, 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 as I remove the effects of economy-wide shocks.

My results indicate that shocks to dominant firms spillover geographically. Specifically, the results indicate a positive correlation between dominant firms' shocks and the future shocks to other local firms. In economic terms, a one standard deviation increase in the magnitude of dominant firms' productivity shocks causes a 49 basis point increase in the standard deviation of shocks to local non-dominant firms in the following year.[5] Considering the average productivity growth of non-dominant firms (i.e. 4.4%), 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 the geographic spillover of shocks from dominant firms to other neighboring firms. To this end, I first study the role of intra-sector trade links. Through this channel, I expect a higher level of geographic cascade effects on non-dominant firms that operate in the same industry as dominant firms. The result confirms the role of intra-sector connections. More precisely, restricting the sample to dominant and non-dominant firms that operate in the same industry increases the geographic cascade effect from 49 basis points (in the baseline analysis) to 2 percentage points. This result is in line with prior studies (e.g. Acemoglu et al. (2012); Cohen and Frazzini (2008)) that show the effects of intra-sector links in propagation of shocks.

While the intra-sector linkage is an important economic channel for shock propagations, it may not be the only channel. To show that geographic spillovers are not *exclusively* driven by intra-sector links, I perform three tests. First, I restrict the sample to local non-dominants that do not operate in the same industry as the dominant firm(s). I find that the geographic spillover effects remain both statistically and economically significant. Second, I use Hoberg and Phillips (2016)'s TNIC data and exclude dominant and non-dominant firm pairs that have overlapping business operations, despite not operating in the same industries. The

[5] The spillover effect dampens to 30 basis points in *t+2*.

effects are similar even when I exclude these firms. Third, 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 economic connections between 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 can vary from one region (or, dominant firm) to another. Despite this potential heterogeneity, I focus on the role of *state income tax payments* and *sectoral connections* as key mechanisms of the geographic cascade effect. I focus on these two channels because they are applicable across nearly all dominant firms.

Dominant firms have considerable effects on the economic growth of their headquarter states.[6] One way for such an impact is through their state income tax payments. Every year, on average, a dominant firm pays $42 million income taxes to its local government. Subsequently, local governments use this financial source to develop state infrastructure. This local development can positively impact the growth opportunities available to local non-dominant firms (Levine (1997); Firebaugh and Beck (1994)). Therefore, I expect the geographic spillovers to be higher in states where dominant firms pay a higher amount of income taxes to the local government. My empirical results suggest that the tax channel is important. All else equal, the spillover effect increases to one percentage point in states where dominant firms pay more taxes to their local governments.

Additionally, to highlight the role of tax channel, I perform a placebo test. Specifically, I restrict the sample to states with no income taxes (i.e. Alaska, Florida, Nevada, South Dakota, Texas, Washington, and Wyoming). If state income tax payments is a valid economic channel for geographic spillovers, it should mostly matter in states where firms are required to pay income taxes. Consistent with this conjecture, I find that the tax channel does not affect the geographic spillovers in states with no income taxes.

Next, motivated by the evidence in Menzly and Ozbas (2010), I study the role of sectoral connections on the geographic cascade effect. Even in the absence of direct links between dominant and non-dominant firms, their sectors can have business interactions. To study the effects of these (implicit) interactions, I use the Input/Output data available on the BEA. Consequently, I follow Fan and Goyal (2006)'s method and define sector connections as cases

[6]For instance, productivity shocks to General Electric and United Technologies, the only two dominant firms in Connecticut, explain more than 17% of the state's GDP growth.

that (despite any direct links between firms) a non-dominant firm's industry receives more than 5% of its total inputs from a dominant firm's sector. The results provide supporting evidence for the role of this economic channel. All else equal, local non-dominants with sectoral connections to dominant firms experience a 46 basis point larger shock spillover.

Overall, the results indicate that shocks to dominant firms cause geographic cascade effects. These spillovers can happen through explicit connections (such as intra-sector trade linkages), or implicit interactions (such as tax payments, or sectoral connections) between firms. For robustness, I show that geographic spillovers are not driven by the effects of common local shocks.[7] Moreover, I show that the results are not driven only by a few number of states with the highest agglomeration of dominant firms (i.e. CA, TX, IL, and NY). The results also stay robust when I use alternative industry classifications. Additionally, I find consistent results when I exclude merger activities from the sample and when I use total factor productivity (TFP) to measure firms' productivity shocks.

In the next step, I examine the asset pricing implications of my findings. Given that productivity shocks to dominant firms contain information about the future fundamentals of local non-dominant companies, 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 longs (shorts) non-dominant firms in states where the productivity shocks to dominant companies are the largest (lowest). This portfolio generates a monthly alpha of 37 basis points, which translates into an annual risk-adjusted excess performance of 4.5%.[8] This performance is robust to the choice of a risk-adjustment model.

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' productivity shocks. 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 the shocks to largest U.S. firms.

[7]Specifically, I find consistent evidence when I adjust firms' productivity shocks to the effect of state-level shocks. I also find similar results when I control for the role local business cycle measures using the economic activities index of Korniotis and Kumar (2013).

[8]This result increases to 7.3% when I condition the performance on size.

The collective evidence suggests that productivity shocks to dominant firms cascade across other local firms. This spillover effect is not restricted to direct economic links. The geographic spillover of shocks from dominant to other local firms have economic implications. For instance, it provides a mechanism through which shocks to the largest firms in the economy aggregate, and subsequently affect the U.S. business cycle (Gabaix (2011)). Moreover, the results identify a source of systematic information that impact firms' local risk.

These results contribute to several strands of Finance literature. First, there is a rapidly growing literature examining the propagation of firm-specific shocks (Gabaix (2011); Kelly et al. (2013); Acemoglu et al. (2016) Baqaee and Farhi (2017); Bernile et al. (2016); Foerster et al. (2011); Wu (2016)). I extend this literature by showing that firms' geographic networks are a channel through which large firms influence other firms. These effects are beyond previously identified shock spillovers via direct economic connections such as customer-supplier links.

This paper also contributes to the literature that documents the importance of geography in the distribution of information about firms (Garcia and Norli (2012); Bernile et al. (2016); Becker et al. (2011); Coval and Moskowitz (1999); Hong et al. (2005); Addoum et al. (2015)). In particular, Pirinsky and Wang (2006) show that there is considerable return comovement among firms headquartered in the same local region. I complement this literature by identifying a new source of information about local firms, i.e., productivity shocks to geographically-proximate large firms.

Finally, I expand the literature on investor inattention (Hirshleifer and Teoh (2003); Hirshleifer et al. (2011); Hong and Stein (1999); DellaVigna and Pollet (2009); and Menzly and Ozbas (2010)). For example, Cohen and Frazzini (2008) argue that investors do not pay attention to the direct connections among companies. Complementing 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.

The rest of the paper is organized as follows. Section 2 presents the main testable hypotheses. Section 3 describes different data sources used in the empirical analysis, and illustrates the estimation strategy. Section 4 reports the evidence related to the geographic spillover of dominant firms' shocks. In Section 5, I present the results related to investors' behavior. I conclude the paper in Section 6.

2 Hypothesis Development

In this section, I formalize the testable hypotheses. I use a stylized model that, unlike the previous studies, builds on a geographic shock propagation caused by a small number of firms (i.e. dominant firms). This specification better identifies sources of public information that market participants overlook, which subsequently results in mis-pricing. Motivated by the main research question of the study, the model also considers a positive correlation between dominant and non-dominant firms' idiosyncratic shocks. In what follows, I show the significance of this correlation and explain how it can result in a larger geographic cascade effect.

2.1 A Stylized Model

To illustrate the effects of dominant firms on local non-dominant companies, I propose a stylized model. The main goal of this section is to show that relaxing the assumption of shocks' independence results in a larger geographic spillover. To this end, I use a framework similar to Parsons et al. (2016) and outline the model assumptions. Next, I explain the model's timing followed by the main testable hypotheses.

The model has three dates t_0, t_1, and t_2. The interest rate is equal to zero and all investors are risk neutral. There are two types of firms in the economy: a dominant firm (D) and a non-dominant company (ND). Both firms are headquartered in the same state (X), but operate in different industries (A and B). In addition to a firm's specific shocks (ε), there are two sources of common variation: industry (I) and regional (L) factors. Firms in one location (industry) realize the same local (industrial) factor.

At each time, each firm realizes an idiosyncratic productivity that affects the company's liquidity dividend (i.e. Π_i^t). Considering the role of sectoral and regional factor, we can decompose Π_i^t as: $\Pi_D^{t(0,1,2)} = I_A + L_X + \varepsilon_D$ for the dominant firm, and $\Pi_{ND}^{t(0,1,2)} = I_B + L_X + \varepsilon_{totalND}$ for the non-dominant company. As explained earlier, I relax the independence assumption of firms' specific shocks. Specifically, $\varepsilon_{totalND} = \beta\varepsilon_D + \varepsilon_{ND}$, where $\beta > 0$, and $corr(\varepsilon_D, \varepsilon_{ND}) = 0$. This conjecture motivates the first hypothesis of the study:

Hypothesis 1: There is a positive correlation between dominant and non-dominant firms' idiosyncratic productivity shocks. Specifically, dominant firms' shocks contain systematic information relevant for geographically close non-dominant companies.

I consider the following distributions for the variables: $I_A \sim N(0, \sigma_{IA}^2)$; $I_B \sim N(0, \sigma_{IB}^2)$; $L_X \sim N(0, \sigma_{LX}^2)$; $\varepsilon_D \sim N(0, \sigma_D^2)$, and $\varepsilon_{totalND} \sim N(0, \beta^2\sigma_D^2 + \sigma_{ND}^2)$. At time $t = 0$, the expected liquidation dividends for both firms, and therefore the prices, are zero, $P_D^0 = P_{ND}^0 = 0$. At $t = 1$, the dominant firm announces the company's profitability. Based on the model's assumption, the productivity factor of the dominant firm, and therefore its liquidity dividend ($\Pi_D^{t=1}$), contains information that can be used to update the price of the non-dominant firm at $t = 2$. At $t = 2$, $\Pi_{ND}^{t=2}$ is realized and the model ends. The agent observes the information in $\Pi_D^{t=1}$ with a probability of p and updates his expectation about the non-dominant firm's productivity with a probability of q, where these two probabilities are independent. My goal is to find the updated price of the non-dominant firm at time $t = 1$ (i.e. $\Pi_{ND}^{t=1}$), using the information contained in the dominant firm's productivity.

$$P_{ND}^{t=1} = E(\Pi_{ND}^{t=2}|\Pi_D^{t=1}) = p(1-q)E(\Pi_{ND}^{t=2}) + pq\Pi_D^{t=1}(\frac{\sigma_{LX}^2 + \beta^2\sigma_D^2}{\sigma_{IA}^2 + \sigma_{LX}^2 + \sigma_D^2}) \tag{1}$$

Therefore:

$$\Pi_{ND}^{t=1} = pq\Pi_D^{t=1}(\frac{\sigma_{LX}^2 + \beta^2\sigma_D^2}{\sigma_{IA}^2 + \sigma_{LX}^2 + \sigma_D^2}) \tag{2}$$

Shock spillover happens if:

$$Cov(P_D^{t=1} - P_D^{t=0}, P_{ND}^{t=2} - P_{ND}^{t=1}) > 0 \tag{3}$$

or

$$Cov(\Pi_D^{t=1} - \Pi_D^{t=0}, \Pi_{ND}^{t=2} - \Pi_{ND}^{t=1}) > 0 \tag{4}$$

As a result:

$$\begin{aligned} Cov(\Pi_D^{t=1}, \Pi_{ND}^{t=2} - \Pi_{ND}^{t=1}) = Cov(\Pi_D^{t=1}, \Pi_{ND}^{t=2}) - Cov(\Pi_D^{t=1}, pq\Pi_D^{t=1}\frac{\sigma_{LX}^2 + \beta^2\sigma_D^2}{\sigma_{IA}^2 + \sigma_{LX}^2 + \sigma_D^2}) = \\ (\sigma_{LX}^2 + \beta^2\sigma_D^2) - pq(\sigma_{IA}^2 + \sigma_{LX}^2 + \sigma_D^2)(\frac{\sigma_{LX}^2 + \beta^2\sigma_D^2}{\sigma_{IA}^2 + \sigma_{LX}^2 + \sigma_D^2}) = \\ (\sigma_{LX}^2 + \beta^2\sigma_D^2)(1 - pq) \end{aligned} \tag{5}$$

As shown in Equation 5, the correlation between dominant and non-dominant firms' specific shocks (i.e. β) results in a higher level of geographic cascade effect. Moreover, this spillover is not restricted to firms' intra-sector linkages, as dominant and non-dominant firms (in the model) do not share the same industrial factor. This finding motivates the second hypothesis of the study:

Hypothesis 2: The geographic shock spillover from dominant to non-dominant companies does not simply reflect explicit/direct linkages between firms.

Finally, Equation 5 suggests that the geographic spillover of shocks from dominant to local non-dominant companies further increases when agents are less likely to observe (captured by p), or react (captured by q) to the information contained in dominant firms' lagged productivity shocks. This finding motivates the following hypothesis:

Hypothesis 3: Spillover effect is decreasing with respect to the probability that agents observe the correlation between dominant and non-dominant firms' shocks.

3 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 compute firm-specific shocks.

3.1 Data Sources

I utilize multiple data sources to construct a state-year level panel. To obtain information on firm-specific shocks and HQ states, I use the Fundamental Annual section of Compustat North America database. I use the Fama-French 48 industry portfolios to identify firm industry. I complement this classification with the text-based network industry classification (TNIC) from Hoberg and Phillips (2010) and Hoberg and Phillips (2016).

National and state-level GDP, as well as information on industries' input/outputs are from the Bureau of Economic Analysis (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 dollars from 1995 to 1997. I use available changes in quantity indices to extend the out of state GDP series in 1997 dollars backwards. I then convert the pre-1997 real chained GDP series from 1997 to 2009 chained dollars by using the ratio of 2009 dollars GDP to 1997 dollars in 1997, where both series are available.

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

3.2 Variable Description

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

3.2.1 Dependent Variables

I use three main dependent variables in the analysis: *Productivity Shocks*, *Non-Dominant Firms' Fundamentals*, and *Analysts' Forecast Errors*. I start with the illustration of firm-specific shocks. Next, I explain the variables related to firms' fundamentals and equity analysts' forecast errors.

I. Productivity Shocks

The primary dependent variable is non-dominant firms' *Productivity Shocks*. I follow Gabaix (2011) to identify dominant and non-dominant firms, as well as their productivity shocks. In particular, dominant firms are the top 100 largest companies in the U.S. based on their prior year's net sales. All other firms are classified as non-dominant firms. Next, I measure a firm's productivity growth as the annual log change in the firm's net sales per employee. Specifically, a firm's productivity is:

$$z_{j,t} = Ln(\frac{Net\ Sales_{j,t}}{Employees_{j,t}}) \tag{6}$$

Subsequently, I compute productivity growth as:

$$g_{j,t} = z_{j,t} - z_{j,t-1} \tag{7}$$

To obtain the firm-specific component of the productivity growth, I extract the effects of common shocks. To do so, I de-mean $g_{j,t}$ from the average of other firms' productivity growth:

$$\widehat{\xi_{j,t}} = g_{j,t} - \bar{g}_t \tag{8}$$

Assuming that the total productivity of the economy is the cumulation of firms' net sales (Gabaix (2011)), I then scale $\widehat{\xi_{j,t}}$ using the ratio of the firm's net sales ($S_{j,t-1}$) to total GDP (Y_{t-1}). This way, a dominant firm that accounts for a bigger portion of GDP receives a higher weight in the analysis (Gabaix (2011); Foerster et al. (2011)). Specifically:

$$Scaled\ Shock_{j,t} = \frac{S_{j,t-1}}{Y_{t-1}} \widehat{\xi_{j,t}} \tag{9}$$

In all specifications, I use an annual measure of firm shocks for two reasons. The main reason is data limitation at higher frequencies. Specifically, Compustat does not provide quarterly information of firms' number of employees. In addition, as argued by Parsons et al. (2016), geographic diffusion of information tends to be slower compared to the likewise industry effects. Given that I aim to document shock propagation beyond explicit intra-sector relations, annual data better allows for the 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 B1. In this table, for some of the dominant firms in the sample, I provide a comparison between the estimated shocks and the nature of the events that happened to the dominant companies.[9] For example, using the explained measure, I compute a productivity shock equal to -10.07% for "HCA Healthcare," a dominant firm headquartered in North Carolina. According to the company's 10-K and 8-K filings, in 1999, the company was involved in a fraud case and also had a growing number of uninsured and reimbursement pressures. Moreover, the measure yields shocks equal to 8.4% for "Rockwell Automation," a dominant firm headquartered in Wisconsin. The company's filings show 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 B1, provide further evidence on the accuracy of the statistical measure.[10]

II. Firm Fundamentals

To understand the economic significance of the geographic shock propagation, I study the effects of a non-dominant firm's shocks on the company's *Earnings*, *Sales*, and *Cash Flows*. Following the previous studies, I define a firm's *Earnings* as the operating income after depreciation divided by the firm's total assets. *Sales* are the net sales of the firm, and *Cash*

[9] The detailed information about the events is provided in the Appendix **??**.

[10] See Gabaix (2011) for more information on the statistical performance of this measure.

Flows are the cash flows from operating activities divided by the total assets (Richardson et al. (2005); Addoum et al. (2015)).

III. Analyst Forecast Errors

Finally, to examine analysts' understanding of the effects that dominant firms have on non-dominant firms, I use an annual average of analyst quarterly earnings *Forecast Errors* and *Accuracy*. I use this measure, as previous studies (e.g. Matsumoto (2002)) point to a higher level of bias in analysts' annual earnings forecasts. However, the results are not sensitive to this choice. I define an analyst's quarterly forecast errors as:

$$Forecast\ Errors_{i,j,q} = \frac{Value_{i,j,q} - Actual_{j,q}}{Price_j} \tag{10}$$

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 $firm_j$, two days before the analyst's forecast date, where forecast date is the most recent forecast of the analyst (Hong and Kubik (2003); Lim (2001); Bondt and Thaler (1990)). Positive forecast errors identify cases where the analyst carries an optimistic opinion about the firm, while negative forecast errors indicate that the analyst is pessimistic about the company's performance.

I define an analyst's accuracy as the absolute value of the forecast errors (Hong and Kubik (2003)):

$$Accuracy_{i,j,q} = |\frac{Value_{i,j,q} - Actual_{j,q}}{Price_j}| \tag{11}$$

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

3.2.2 Explanatory Variables

To control for a firm's profitability and growth opportunities that can potentially translate into the firm's productivity, I use the following variables: *Size*, *Leverage*, *Loss*, *Market-to-Book*, and *Dividend Yield*. I also control for the firm's lagged productivity shocks to ensure that the shock propagation is beyond the lagged 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 a value of one when operating income (dividend) is negative, and zero otherwise. *Market-to-Book* is the sum of market equity, short-term debt, and long-term debt, divided by the total assets. *Dividend Yield* is dividends divided by shareholders' equities. In the earnings analysis, I include *Lagged*

Earnings in the specification, as prior studies show that firms' earnings are persistent (see Addoum et al. (2015)).

When studying analysts' behavior, I control for attributes that can affect their earnings forecasts. Specifically, I include a series of variables to control for analysts' *Experience*, *All-star* position, *Location*, *Brokerage Size*, and *Excess Information*.

Experience is a dummy variable set to one if an analyst, at a specific point in time, has more than three years of presence in the sample (Hong and Kubik (2003)). To proxy for analyst geographic proximity, I define a dummy variable, *Local-analyst*, set to one if the analyst's brokerage is located in the same state as the firm he covers (Malloy (2005)). *All-star* is a dummy variable set to one if the analyst is ranked among the II All-Americans in the previous year. *Brokerage Size* is equal to $log(1 + analysts\ number)$, where analyst number shows the total number of analysts that work in the brokerage (Kumar (2010); Huang et al. (2014)). Finally, to control for the analyst's additional information about dominant companies, I include a dummy variable, *Both-cover*, set to one if, in addition to the local non-dominant firm, the analyst had also covered the dominant firm in the prior year.

3.3 Sample Formation and Estimation Strategy

I take a number of steps to build the final sample. First, I exclude companies not located in the U.S. I also filter out oil and oil-related companies (SIC codes 2911, 5172, 1311, 4922, 4923, 4924, and 1389) as well as energy firms (SIC codes between 4900 and 4940). I do so because the fluctuations of these firms' sales are mostly affected by worldwide commodity prices rather than productivity shocks. I also exclude financial firms (SIC code between 6000 and 6999) because financial firms' sales do not coincide with the underlying economic meaning of the measure used in this paper (See Gabaix (2011)). I also require that firms have sales and employee data available for the current and previous years.

To form the analysts' sample, I exclude analysts with 0 or unknown identification codes. 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); and Grinblatt et al. (2016)). The final sample contains a total 225 dominant and 7,113 non-dominant companies between 1995 to 2015.

To estimate the effects of dominant firms' shocks on the local non-dominant firms, I build a pooled panel database. Specifically, for every dominant firm, I identify all non-dominant companies that are headquartered in the same state. I use the pooled panel, as it allows me to correctly study the effects of a dominant firm on out-of-sector non-dominants. [11] However, creating the panel this way may raise the concern of 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 (1987) method with a 6-year lag (Ortiz-Molina and Phillips (2014)).[12] To additionally ensure that the results are not sensitive to the repeated values in the pooled panel, I replicate the results for Fama and Macbeth (1973) regression, where I use the weighted average of dominant firms' shocks as the main independent variable.[13]

3.4 Summary Statistics

Figure 2 shows the geographic distribution of dominant firms. For each state I show firms, that at some point in the sample, are identified as a dominant company. Figure 2 shows large firms such as Coca-Cola, Microsoft, Intel, Alphabet, among others. The geographic distribution indicates that New York, California, Illinois, and Texas have the highest agglomeration of dominant firms.

I report the summary statistics of the main variables for dominant and non-dominant firms in Panel A and B of Table 1, respectively. Reported statistics are comparable to the prior studies (e.g. Addoum et al. (2015); and Frank and Goyal (2009)). As shown, non-dominant firms have a higher level of volatility in productivity shocks (44% vs. 12% for dominant firms). This pattern holds with respect to firms' cash flows and leverage measures.

Also, dominant firms' net sales and number of employees are well above those of non-dominant companies. On average, dominant firms have net sales of \$19.3 billion, while this number is \$871 million for non-dominant firms. This difference is also highlighted in companies' state tax payments. On average, dominant firms yield \$43 million to their local

[11] To further illustrate the reason, assume that in state X, there are two dominant firms, A and B, as well as 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-dominants, I exclude the effects that A might have on C, but still consider the possible effects of B on C. A pooled panel set-up allows me to examine such effect.

[12] The estimation results remain identical if I choose the lag equal to 5 (or 4) years similar to Parsons et al. (2016) and the method suggested in Bali et al. (2016). However, I choose the lag of 6 years following Watson (2008)'s suggestion (see 2008 NBER summer lectures). Further investigation of data also supports the persistence of dominant firms' shocks. For example, the effects of 2000 negative shocks to Textron (see Table B1) shows up more than 5 years later in the company's 10-K filing.

[13] I also replicate the results using pooled OLS that includes state and year FE and adjust the standard errors at the non-dominant firms+year level Petersen (2009).

governments, while this number is less than \$3 million for non-dominant companies. Finally, Panel C of Table 1, reports the correlation among the main variables of interest. Time-lagged shocks of dominant firms positively correlate with the firm-specific shocks of non-dominant companies that operate in different industries. This correlation is significant at the 5% level. In the next section, I show that this correlation results in a significant geographic spillover of shocks.

4 Geographic Spillover of Idiosyncratic Shocks

This section presents the main empirical findings. I start the analysis by showing the propagation of shocks from dominant firms to local non-dominant firms. I show that while intra-sector trade links are an important economic channel for the shock propagation, the spillover effect is not exclusively driven by these linkages. Next, I illustrate alternative economic channels (based on implicit interactions of firms) for geographic spillovers and discuss the economic significance of the results. I end this section by providing multiple robustness tests.

4.1 Baseline Results

I start the analysis by examining whether productivity shocks to dominant firms spillover to geographically close firms. To this end, each year, I compute shocks to dominant and non-dominant firms using the method explained in Section 3. Next, I run the following predictive Fama and Macbeth (1973) regression. I use Fama and Macbeth (1973)'s method because it implicitly controls for time variation in market-wide conditions (see Campbell and Shiller (1988)).

$$\textit{Non-Dominant Shocks}_{t+1} = \alpha + \beta_1\, \textit{Dominant-Firm's Shocks}_t + \beta X_t + \varepsilon_{t+1} \tag{12}$$

From the above regression, I am interested in estimation of β_1, which shows the predictive power of a dominant firm's shocks on a non-dominant firm that is headquartered in the same state. In all specifications, I control for a vector of variables (X_t) that can affect a non-dominant firm's productivity.[14] [15]

[14] Specifically, I control for the firm's cash flows, leverage, dividend yield, market-to-book ratio, loss, and size.

[15] Results stay consistent, if I additionally control for dominant firm's contemporaneous productivity shocks (i.e. $\textit{Dominant-Firm's Shocks}_{t+1}$)

Column 1 of Table 2 reports the estimates considering the sample of all non-dominant firms that are headquartered in the same state as the dominant firm. As shown, above the effect of non-dominant firms' profitability, shocks to dominant companies significantly predict productivity shocks to local non-dominant firms. In economic terms, a one standard deviation increase in dominant firms' productivity shocks causes a 49 basis point increase in the next period productivity shocks to local non-dominant firms (coefficient=0.0049, t-statistic=2.46).[16] Considering the average productivity growth of non-dominant firms (i.e. 4.4%) this effect is economically significant.

Another finding of Table 2 is the effect of the geographic shock spillover on small non-dominant firms. The results in Column 1 of Table 2 indicate that, all else equal, the shock spillover has a stronger effect on smaller sized non-dominant firms (coefficient=-0.0307, t-statistic=-3.08). This result is in line with the findings in Wu (2016), that shock propagations have a stronger effect on firms with a weaker market power. Together, these results support the first hypothesis of the study; that shocks to the largest firms in the economy create a geographic cascade effect.

Next, I study the role of intra-sector trade links as a channel for the geographic spillover. To do so, I restrict the sample to dominant and local non-dominant firms that operate in the same industry. Consequently, I repeat the same regression as in Equation 12. Column 2 of Table 2 shows the estimation results. The results indicate that this restriction increases the economic magnitude of the geographic spillover from 49 basis points to 2.02 percentage points (coefficient=0.0202, t-statistic=2.02). This result is in line with the prior studies (e.g. Acemoglu et al. (2012), Cohen and Frazzini (2008)) that demonstrate the role of firms' intra-sector links in transmission of shocks. While intra-sector connections between dominant and non-dominant firms are economically important, dominant firms may also affect other neighboring firms despite a lack of intra-sector connections. I examine this hypothesis in the next section.

4.2 Geographic Spillovers to Out-of-Sector Firms

In this section, I test the second hypothesis of the study. Specifically, I aim to show that geographic spillovers are not only restricted to intra-sector trade links. To further demonstrate dominant firms' impact, beyond industry linkages, I provide an example in Figure 3. The

[16] Reported estimates are all beta coefficients (i.e. they are standardized).

upper part of Figure 3 shows the effect of a negative shock to Sprint, a large U.S. company in the "Communication" industry, headquartered in Kansas. This negative shock happened in 2005 followed by the merger experience of Sprint with Nextel.[17] In the same year, Textron, a large U.S. firms in the "Aircraft" industry headquartered in Rhode Island, experienced a positive productivity shock followed by a significant boost in its product demands.

As shown in Figure 3, Kansas non-dominant firms that operated outside of the Communication industry considerably underperformed the market over 2005 and 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 large firms can eventually propagate to other local firms, even in the absence of intra-sector connections.

To test the above conjecture, I perform three tests. First I examine the shock spillover from dominant firms to out-of-sector non-dominant firms. Next, I additionally remove intra-market connections. Finally, I study the effects of direct trade links (through customer-supplier connections) on the main results.

4.2.1 Excluding Intra-Sector Links

In Column 3 of Table 2, I exclude non-dominant firms that operate in the same industry as dominant companies. As shown in Table 2, this restriction declines the size of the coefficient (β_1 in Equation 12) from 49 to 33 basis points. Despite this decline, dominant firms' shocks still significantly predict productivity shocks to out-of-sector non-dominant firms (coefficient=0.0033, t-statistic=2.26).

This result provides supporting evidence for the second hypothesis of the study; that the geographic spillover of shocks from dominant to local non-dominant firms is not restricted to the intra-sector connections.

4.2.2 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 text-based network industry classification (TNIC) data from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). Using firms' 10-K filings, TNIC provides a *score* that captures the similarity of firms' product markets. Compared to the SIC, TNIC provides a better classification of

[17] Specifically, the merging was not a successful experience for Sprint due to many difficulties at the operational level.

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' explicit 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, while not sharing the same industry, have a positive similarity *score*. This exclusion should remove any remaining interactions due to the 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).

4.2.3 Excluding Customer-Supplier Links

In the previous sections, I used firms' industries and product markets to capture their intra-sector trade links. However, companies might have *direct* connections outside of their sectors. These interactions can potentially confound the above conclusion that the geographic shock spillover does not simply reflect firms' explicit relations. To study the impact of these direct linkages, I use the customer-supplier data from Cohen and Frazzini (2008). Next, I identify and exclude dominant and non-dominant pairs that, while not sharing a similar sector/marketplace, have a supplier (or customer) connection.[18] The estimates in Column 2 of Table 3 show that the 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, one could argue that the above identification may not completely capture firms' direct linkages. To additionally show that the geographic spillover is not restricted to the effect of customer-supplier links, I exclude dominant firms that operate in industries with a high level of out-of-sector interactions (i.e. 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.[19] Subsequently, I repeat the same analysis, excluding dominant firms that work in one

[18] According to the SFAS No. 131 regulation, companies are required to report the identity of customers that account for more than 10% of their total sales. Using firms' financial reports, Cohen and Frazzini (2008) identify customer-supplier links for the sample of companies available on the CSRP Compustat database.

[19] These sectors are: Construction Materials; Construction; Electrical Equipment; Health care; Personal Services; Consumer Goods; Restaurants, Hotels, Motels; Textiles; Agriculture; Precious Metals; Tobacco Products; Business Supplies; Printing and Publishing; Entertainment; Shipbuilding, Railroad Equipment; Shipping Containers; and Candy & Soda

of these sectors. As shown in Column 3 of Table 3, results are also robust to this exclusion (coefficient=0.0043, t-statistic=2.11).

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

4.3 Alternative Economic Linkages

Dominant firms can have considerable effects on their local economies. In Appendix C, I show that productivity shocks to dominant firms explain a considerable portion of the business cycle of their headquarter states. 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 effect is more than 80% in Idaho. The influence of dominant firms on their local economies can happen via multiple channels (see Figure 1). In this section, I focus on dominant firms' state income tax payments as a channel through which, large firms affect the economic growth of their local areas. This effect can in turn impact the growth opportunities for other neighboring firms.

4.3.1 State Income Taxes

State income tax payments of dominant firms is a financial source for their local governments. For example, according to Delta's website, in 2013 the company paid $300 million to Georgia's government through taxes and fees. Local governments use state income taxes to assist and subsidize local firms and to develop the infrastructure of their local economies. This development positively affects the growth opportunities of local firms. Therefore, through this channel I expect a higher level of cascade effect in states where dominant firms pay a higher level of taxes to their local governments. To test this hypothesis, I collect dominant firms' state income taxes from Compustat. Using the actual tax paid, I *proxy* for the tax that dominant firms pay to their headquarter states. Specifically:

$$State\ Tax = \frac{Total\ Tax\ Paid}{Total\ Income\ Tax} \times Income\ State\ Tax \tag{13}$$

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

$$\begin{aligned} \textit{Non-Dominant Shocks}_{t+1} = \alpha + \beta_1\, \textit{Dominant-Firm's Shocks}_t + \beta_2\, \textit{State Tax}_t + \\ \beta_3\, \textit{Dominant-Firm's Shocks}_t \times \textit{State Tax}_t + \beta X_t + \varepsilon_{t+1} \end{aligned} \tag{14}$$

The results in Column 3 of Table 4 confirm the role of tax channel in transmission of productivity shocks. In particular, all else equal, in states where dominant companies pay a higher level of taxes, local non-dominant firms experience a larger shock spillover (coefficient=0.0074 t-statistic=2.23).[20] In Column 4 of Table 4 I additionally control for the size of revenues that different local governments generate out of corporate taxes. To do so, I substitute the state tax payments in Equation 13 with $\frac{\textit{State Tax}_{j,s}}{\sum_{j=1}^{N} \textit{State Tax}_{j,s}}$, and repeat the same analysis.

The results in Column 4 of Table 4 show consistent evidence as prior estimates. Overall, this analysis shows that in addition to explicit interactions between firms, implicit connections can also be economically important.

In Appendix D I show the role of sectoral connections as another economic channel for the geographic spillover. This channel also shows the impact of implicit interactions between firms in propagation of shocks.

4.4 Economic Significance of Geographic Spillovers

In the previous sections, I identified the impact of dominant firms' shocks on local non-dominant firms. What remains unanswered is the economic importance of this finding.

To understand the importance of a productivity shocks I study the effects of such shocks on a series of firms' fundamentals including earnings, sales, and cash flows. This analysis mainly captures the effects of dominant firms' shocks on non-dominant firms' fundamentals, through the influence that large firms have on non-dominant firms' productivity (i.e. $\textit{Dominant-Firm's Shocks}_{t-1}$ to $\textit{Non-Dominant Shocks}_t$, and then $\textit{Non-Dominant Shocks}_t$ to $\textit{Non-Dominant Fundamentals}_t$).

Table 5 reports the results for the following Fama and Macbeth (1973) regressions:

$$\textit{Non-Dominant Earnings}_t = \alpha + \beta_1\, \textit{Non-Dominant Shocks}_t + \beta X_{t-1} + \varepsilon_t \tag{15}$$

[20] The results stay similar if I exclude states with no income taxes (i.e. Alaska, Florida, Nevada, South Dakota, Texas, Washington and Wyoming).

$$Non\text{-}Dominant\ Sales_t = \alpha + \beta_1\ Non\text{-}Dominant\ Shocks_t + \beta X_{t-1} + \varepsilon_t \tag{16}$$

$$Non\text{-}Dominant\ Cash\ Flows_t = \alpha + \beta_1\ Non\text{-}Dominant\ Shocks_t + \beta X_{t-1} + \varepsilon_t \tag{17}$$

Column 1 of Table 5 shows the effect of firm's productivity shocks on earnings. As shown, productivity shocks positively affect the company's earnings.[21] Specifically, a one standard deviation increase in the firm's specific shocks corresponds to a 1.5 percentage points increase in the contemporaneous earnings (coefficient=0.0152, t-statistic=5.08).

Column 2 of Table 5 reports the regression results for the net sales analysis (Equation 16). Similar to the earnings, firm-specific shocks positively and significantly affect the firm's net sales. In particular, a one standard deviation increase in the firm-specific shocks increases the firm's contemporaneous sales more than 3.7 percentage points (coefficient=0.0368, t-statistic=2.19). Finally, Column 4 of Table 5 shows the analysis for firm's cash flows (Equation 17). Similar to the prior effects, firm specific shocks also positively affect the firm's cash flows. A one standard deviation increase in the firm-specific shocks increases contemporaneous cash flows more than 2.7 percentage points (coefficient=0.0266, t-statistic=2.33).[22] Overall, the analysis in this section show the significance of the geographic shock spillover on non-dominant firms' fundamentals.

4.5 Robustness Checks and Alternative Explanations

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

4.5.1 Aggregating Dominant Firms' Productivity Shocks

As explained in Section 3.3, 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, due to the repeated values in the pooled panel. I choose the Fama and Macbeth (1973) regression to mitigate this possibility. However, to ensure that the results are not affected by this concern, I repeat the baseline analysis by

[21] Consistent with the prior research, I also find evidence for the persistence of firms' earnings, as the estimated coefficients on the lagged firms' earnings are positive and statistically significant (Addoum et al. (2015); Dichev and Tang (2009)).

[22] Results stay similar, if I use pooled OLS with year and state FE, and standard errors that are clustered at year+firm level Petersen (2009) (Results are available upon request).

aggregating the main independent variable (i.e. dominant firms' productivity shocks). To do so, I use the weighted average of dominant firms' shocks as follows:

$$\Gamma_{s,t} = \sum_{j=1}^{K} \frac{S_{j,s,t-1}}{Y_{t-1}} \widehat{\xi_{j,s,t}} \tag{18}$$

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

$$\textit{Non-Dominant Shocks}_{t+1} = \alpha + \beta_1 \Gamma_{s,t} + \beta X_t + \varepsilon_{t+1} \tag{19}$$

Column 1 of Table 6 reports the regression results. As shown, this aggregation does not affect the outcome (coefficient=0.032, t-statistic=2.29).

4.5.2 Alternative Industry Classification

So far, I have used Fama-French 48 industry portfolios to identify firms' sectors. In this section, I complement this classification with the TNIC data from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). Using this measure, I *reclassify* firms' industries to assure that the baseline results are robust to a different classification. To do so, I define intra-sector firms as pairs that have a similarity score greater than 21.32%. According to Hoberg and Phillips (2016), 21.32% is a minimum similarity threshold that classifies firms in the same industry similar to three-digit SIC codes.

Using this classification, I repeat the baseline analysis of Table 2. The estimates in Column 2 of Table 6 show that using a different industry classification results in consistent outcomes (coefficient=0.0033, t-statistic=2.26).

4.5.3 Propagation of Shocks Across Industries

An alternative explanation for the above findings is the possibility of shock propagation across different industries. For example, one could argue that due to a positive shock to the tech industry, employees of Apple (as a dominant firm in the tech industry) might experience a higher level of salary and subsequently, spend that money to receive services from companies that are outside of the tech industry. Therefore, the positive shock transfers to other out-of-sector companies.

The possibility of shock propagation due to the sectoral connectivity (as documented in Foerster et al. (2011)) is not against the main motivation of this study. In Appendix D, I show evidence on how sectoral connections can facilitate the geographic spillovers (i.e. sectoral connections are also an economic channel for the shocks propagation). However, if shock propagations across different sectors are the primary reason for the geographic spillover, it would raise the question of whether shocks to the dominant firms *cause* the geographic spillover.

To show that shock propagations across different sectors are not exclusively driving the main results, I use an alternative proxy for firms' shocks. To do so, I de-mean firms' productivity growth from the average growth of companies that operate in the same industry (Gabaix (2011)).[23] Specifically, I use the following proxy:

$$\widehat{\xi_{j,t}} = g_{j,i,t} - \bar{g}_{i,t} \tag{20}$$

where $\bar{g}_{i,t}$ shows the average productivity growth of firms among the top 100 firms therein that are in i's industry. Column 3 of Table 6 repeats the baseline analysis using the new proxy. As shown in Table 6, adjusting for the industry-level shocks does not affect the baseline results (coefficient=0.0057, t-statistic=2.05). Consistent with this finding, the results in Appendix D also confirm that while sectoral connections can be a channel for shock spillovers, they are not exclusively driving the effect.

4.5.4 Common Local Shocks

One could argue that the documented spillover is driven by state-level common shocks. By design, the statistical measure used to proxy for firm-specific shocks removes the aggregate productivity growth of other companies. Therefore, the used measure, by large extend, should remove the effects of common shocks. However, to further examine the impact of common local shocks, I adjust firms' productivity growth, using the following proxy:

$$\widehat{\xi_{j,t}} = g_{j,s,t} - \bar{g}_{s,t} \tag{21}$$

[23] The results stay robust if I use the Fama-French 12 industries classification.

where $\bar{g}_{s,t}$ shows the average productivity growth of firms that are headquartered in state s. Columns 4 of Table 6 shows that adjusting for state-level shocks does not affect the baseline estimates (coefficient=0.0084, t-statistic=4.62).

Moreover, I investigate the impact of common local shocks using 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 generated mainly by a *small group* of firms. Motivated by this argument, I focus on states where there are a few number of dominant firms. Specifically, I repeat the analysis on the sample of states that have had (maximum) four dominant firms throughout the sample.[24] The results in Column 5 of Table 6 show that this restriction further increases the economic magnitude of the baseline effects to a 2 percentage points (coefficient=0.0203, t-statistic=2.07).

Further, in an untabulated result, I check the possible impact of state-level common shocks, using Korniotis and Kumar (2013)'s index for states' *Economic Activities*. This index is defined as the sum of state-level income growth and state-level housing collateral ratio, minus the standardized value of the relative state-level unemployment ratio. Therefore, this index should control for the role of state-level economic impact. Controlling for this index results in the same geographic cascade effect.[25]

4.5.5 States with High Agglomeration of Dominant Firms

Additionally, I study whether geographic spillovers are mainly driven by states with high agglomeration of dominant firms. To do so, I exclude NY, CA, TX, and IL which have the highest number of dominant firms (see Figure 2).

Column 6 of Table 6 shows the result that excludes the above states. As shown, this restriction does not decline the spillover magnitude. On the contrary, it intensifies the economic magnitude from 33 (in Table 2) to 73 basis points (coefficient=0.0073, t-statistic=2.15). This increase potentially reflects the effects of shock diversification in the aforementioned states.[26]

[24] These states are shown in Column 2 of Table C1.

[25] Results are available upon request.

[26] In an untabulated result, I also study the role of merger activities. I find consistent evidence for the geographic propagation of shocks when I exclude merger activities from the sample. Results are available upon request.

4.5.6 Economic Activities in Corporate Headquarters

I also study whether the level of firms' economic activities in their headquarter states impact the geographic spillovers. So far, I have used firms' headquarter states to identify geographic networks between dominant and non-dominant firms. Firms, however, may have a different level of economic activities in their headquarter states (Bernile et al. (2016); Addoum et al. (2015)). Therefore, I study whether the geographic spillover of shocks is stronger when dominant and non-dominant firms have a higher economic presence in their corporate headquarters. To do so, I use "Citation Share" data from Bernile et al. (2016) to identify the level of economic presence of firms across the U.S. states.

Specifically, 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 the citation share measure as the number of times a state is cited divided by the total number of citations of all states in the firm's 10-K filing in a specific year. Subsequently, I restrict the sample to dominant and non-dominant firms that their headquarter states have the highest citation share and repeat the baseline analysis. Column 7 of Table 6 shows the estimation result. As expected, the geographic cascade effect increases to 69 basis points (coefficient=0.0069, t-statistic=3.18), which compare to the baseline result is economically and statistically more significant. This result indicates that dominant firms have a stronger economic impact on local non-dominant firms when companies have a higher economic activities in their geographic regions.

4.5.7 TFP as a Measure of Firm Productivity

Finally, I examine the robustness of the baseline results (Column 1 of Table 2) to another measure of firm productivity. To do so, 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 ($y_{i,t}$),[27] İmrohoroğlu and Tüzel (2014) estimate firms' TFPs ($w_{i,t}$), using a semi-parametric procedure for the following equation:

$$y_{j,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + w_{i,t} + \eta_{i,t} \tag{22}$$

[27]Specifically, firms' value added is computed as Sales - Materials deflated by the GDP price deflator, where Materials is measured as Total expenses minus Labor expenses. See Appendix A of İmrohoroğlu and Tüzel (2014) for more information.

In the above equation, $\eta_{i,t}$ is an error term not known by the firm or the econometricians. Using the firm-level TFP data, I reestimate firms' productivity shocks following the same method described in Section 3.2.1 and repeat the baseline analysis.

Column 8 of 6 shows the estimation result. As shown using TFP as a measure of firm productivity results in a consistent outcome as the baseline analysis (coefficient=0.0033, t-statistic=2.35).

5 Geographic Spillovers and Asset Prices

Given that productivity shocks to dominant firms contain information about the future fundamentals of local non-dominant companies, 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 market participants' and equity analysts' behavior.

5.1 Geographic Spillovers and Predictable Returns

If stock prices under-react because the value-relevant information in dominant firms' specific shocks aggregate 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 (Equation 18) of dominant firms' shocks headquartered in the state. Specifically, I sort states into deciles (Jegadeesh et al. (2004)), where the 10^{th} decile contains states with the highest (i.e. most positive) weighted average of dominant firms' shocks, and the 1^{st} decile contains states with the lowest (i.e. most negative) weighted average of dominant firms' shocks. Subsequently, I create a zero-cost portfolio that longs all non-dominant companies headquartered in the 10^{th} decile states, and shorts all the non-dominant companies that are headquartered in the states of the 1^{st} decile. Following Fama and French (1993), portfolios' returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$. Returns are calculated beginning in July year t to assure the information related to dominant firms' productivity shocks for year $t-1$ in known to market participants.

Panel A of Table 7, reports the main characteristics of the non-dominant firms located in each group. As shown, non-dominant 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 4.7% to 16.23%. As shown in Table 7, 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 32.01% of the total market shares, covering 18.78% of the U.S. states.

Panel B of Table 7 presents the risk-adjusted performance (i.e. alpha) of the trading strategy. Specifically, I use the following factors: i) CAPM model that uses the market excess return (MKT), ii) the Fama and French (1993) (F-F) three-factor model, which includes the size (SMB), value (HML), and market (MKT) factors, iii) the Carhart (1997) four-factor model, which adds the momentum factor (UMD), and iv) the Pastor and Stambaugh (2003) five-factor model that additionally includes the liquidity factor (LQT). The long-short portfolio performance remains statistically and economically significant when including the various factors to account for risk differences across the portfolios. In particular, CAPM, three, four, and five factor model generate monthly alpha of 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.[28] Overall, the baseline trading strategy suggests that the market does not fully extract the information contained in dominant firms' productivity shocks, which results in generating an annual risk-adjusted performance of over 4.57%. The result remains consistent when I use value-weighted long-short portfolio. More precisely, in Panel C of Table 7 I repeat the same trading strategy using firms' last month market capitalizations as the weighting matrix. Results indicate even a higher abnormal monthly return of 0.605 basis points (7.51% annual return).[29]

Figure 4 shows the diffusion pattern of the unpriced information (contained in the dominant firms' shocks) in the market. Specifically, this figure reexamines the performance of the explained long-short portfolio K months after forming the portfolio. As shown, the risk adjusted alpha (using the five factor model) stays statically significant through the first seven months after creating the long-short portfolio. This result suggests that, on average, it takes seven months for the market to realize the economic impact that dominant firms' productivity shocks have on other local firms.

[28]The result in the first two panels of Table 7 shows the orthogonality to the traditional risk factors, documented also in Parsons et al. (2016). The results show that the difference in the raw returns between the top and bottom deciles (44 basis points) is nearly identical to the intercept estimated from either a regression against the market (43 basis points) or against the three factors (41 basis points).

[29]This economic magnitude is comparable to the effect documented in Menzly and Ozbas (2010).

Next, I test the third hypothesis of the study. Specifically, I examine whether the documented price under-reaction increases when the effects of dominant firms on non-dominant companies are less salient. To test this hypothesis, I repeat the same explained trading strategy on i) the sample of local non-dominant firms that operate in a different industry (than dominant companies), and ii) on non-dominants that share the same industry with 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 under-reaction to the effects of dominant firms on out-of-sector non-dominant firms. As shown in Panel D and E of Table 7 restricting the sample to non-dominants that share the same industries with the dominant firms, results in statistically insignificant alphas in four and five factor specifications. These results suggest that the market is not able to fully react to the geographic impact that the large firms have on the other local businesses. This under-reaction further increases when connections of firms are less salient to investors.

5.2 Geographic Spillovers and Analysts' Behavior

In this section, I study whether sell-side equity analysts, as a group of sophisticated investors, incorporate the information contained in dominant companies' shocks. To this end, I first examine whether analysts recognize shocks to dominant firms, and second if they incorporate the geographic shock spillover from dominant to non-dominant companies.

5.2.1 Analysts and Dominant Firms

To understand whether analysts recognize the impact of productivity shocks to dominant firms, I run the following Fama and Macbeth (1973) regressions:

$$\begin{aligned} Forecast\ Errors_{a,t} = \alpha + \beta_1\, \textit{Dominant-Firm}_{t-1} + &\beta_2 Shocks_{t-1} + \\ \beta_3\, \textit{Dominant-Firm} \times Shocks_{t-1} + \beta X_{i,t} + \delta Z_{a,t} + \varepsilon_{a,t} & \end{aligned} \tag{23}$$

$$\begin{aligned} Accuracy_{a,t} = \alpha + \beta_1\, \textit{Dominant-Firm}_{t-1} + &\beta_2 Shocks_{t-1} + \\ \beta_3\, \textit{Dominant-Firm} \times Shocks_{t-1} + \beta X_{i,t} + \delta Z_{a,t} + \varepsilon_{a,t} & \end{aligned} \tag{24}$$

where $Forecast\ Errors_{a,t}$ shows the annual average of analyst a's quarterly *forecast errors* (Equation 10), *Dominant-Firm* is a dummy variable set to one, if the company covered by the analyst is a dominant firm, $Shocks_{t-1}$ shows the firm's productivity shocks (Equation 9), and *Accuracy* is the annual average of the analyst's forecast accuracy (Equation 11). In the specifications, I control for the firm's ($X_{i,t}$), and the analyst's ($Z_{a,t}$) characteristics.[30]

The results in Columns 1 and 2 of Table 8 show that analysts, on average, have a higher level of forecast errors, and at the same time a lower level of accuracy, when issuing earnings forecasts for dominant firms. This error further increases when I consider the effect of dominant firms' productivity shocks (coefficient=0.0151, t-statistic=2.35).

To additionally, examine whether analysts react to the information contained in dominant firms' shocks, I study their timing strategies in reviling earning forecasts for dominant companies (Ivkovic and Jegadeesh (2004); Agrawal et al. (2006)). Specifically, I run the following regression:

$$\begin{aligned} Forecast\ Age_{a,t} = \alpha + \beta_1\, \textit{Dominant-Firm}_{t-1} + &\beta_2 Shocks_{t-1} + \\ \beta_3\, \textit{Dominant-Firm} \times Shocks_{t-1} + \beta X_i + \delta Z_a + \varepsilon_{a,t} \end{aligned} \tag{25}$$

where $Forecast\ Age_{a,t}$ shows the number of days between the analyst's earnings issuance and the actual announcement date by the firm.

Column 3 of Table 8 shows that analysts, on average, seem to not follow a specific timing strategy when they issue dominant firms' earnings forecasts (coefficient=0.0582, t-statistic= 1.12). This result further suggests that equity analysts do not appropriately account for the information contained in dominant firms shocks. In the next section, I study whether analysts incorporate the information contained in the geographic network between dominant and local non-dominant firms.

5.2.2 Analysts and Geographic Networks

To examine whether analysts account for the geographic shock spillover, I study the effects of dominant firms' lagged shocks on analysts' earnings forecasts. Specifically, I run the following Fama and Macbeth (1973) regression:

$$Forecast\ Errors_{a,i,t} = \alpha + \beta_1\, \textit{Dominant-Firm's Shocks}_{j,t-1} + \gamma X_{i,t} + \delta Z_{a,t} + \varepsilon_{a,i,t} \tag{26}$$

[30]Specifically, I control for the analyst's *brokerage size* (Gu and Wu (2003) and Lim (2001)), *experience* (Hong and Kubik (2003)), *location* (Malloy (2005)), and *All-star* position (Desai et al. (2015)).

The dependent variable is the annual average of analyst a's quarterly *forecast errors* for a non-dominant firm i. The main coefficient of interest is β_1 that captures the analyst's reaction to the lagged shocks to dominant firm j.

Table 9 reports the estimation results. In Panel A, I use the sample of all non-dominant firms that, regardless of their industry classifications, share the same headquarter state with the dominant firm. As shown, a higher level of dominant firms' shocks results in a higher level of errors in analysts' earnings forecasts (coefficient=0.0151, t-statistic=3.68). To examine this further, I separate the impact of dominant firms' positive and negative shocks in Columns 2 and 3. In line with the previous studies (Daniel et al. (1998); and Easterwood and Nutt (1999)), the results indicate that the primary source of the increase in analysts' forecast errors is driven by their under-reaction to negative shocks (coefficient=0.0107, t-statistic=2.62).

In panel B of Table 9, I focus on the effects of dominant firms on out-of-sector non-dominant firms. The results indicate that dominant firms' shocks (positive or negative) load insignificantly on analysts' earnings forecasts. This result suggests that the upward bias in Panel A, is mostly driven by the analysts' optimism towards non-dominant firms that operate in the same industry as dominant companies. Moreover, analysts' different attributes, such as their skill, experience, or additional knowledge about dominant firms, do not affect this lack of attention.

Finally, to examine whether the information contained in the large firms' shocks affects analysts' forecast accuracy, I run the following Fama and Macbeth (1973) regression:

$$Accuracy_{a,i,t} = \alpha + \beta_1 \, \textit{Dominant-Firm's Shocks}_{j,t-1} + \gamma X_{i,t} + \delta Z_{a,t} + \varepsilon_{a,i,t} \tag{27}$$

In the above equation, accuracy is the absolute value of the analyst's forecast errors. Therefore, a lower value of the variable is associated with a higher level of accuracy (Equation 11). Panel C of Table 9 shows that, same as earnings forecast errors, dominant firms' shocks do not have a significant impact on analysts' forecast accuracy.

Local Analysts' Accuracy

The estimates in Panel C of Table 9 indicate that local analysts are the exception for the previous results. Specifically, local analysts gain a higher level of accuracy using the information content of dominant firms productivity shocks. As shown in Panel C of Table 9, a one standard deviation increase in a dominant firm's shocks is associated with a 5.77

percentage point increase in the local analyst's accuracy (coefficient=-0.0577, t-statistic=-4.86). This result is in line with the evidence from Malloy et al. (2006), and Orpurt (2004), that local analysts have access to a superior set of information regarding firms in the same geographic area.

The overall under-reaction of analysts 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 conclude that because analysts are most likely specialized in 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 result suggests that in addition to industry-related skills, analysts could benefit from paying attention to information that highly depends on the geography of firms.

6 Summary and Conclusions

In this paper, I study the firm-level interactions between the largest U.S. firms (i.e. dominant firms) and other firms. Focusing on geographic networks, I find evidence for shock spillovers from dominant to local non-dominant firms. Productivity shocks to non-dominant firms subsequently translate into local firms' earnings, sales, and cash flows and are magnified for small firms. The results indicate that intra-sector trade links is an important economic channel for the spillover. However, the geographic cascade effect is not only restricted to the explicit interactions between firms. I show evidence for the role of state tax payments as an alternative channel for the geographic spillover.

Next, I study whether the market understands this geographic spillover. To do so, I form a series of geographic trading strategies. A zero-cost portfolio that longs non-dominant firms in states with the highest shocks to dominant firms, and shorts non-dominant firms in states with the lowest shocks to dominant firms, generates a positive monthly alpha of 32 basis points, a 3.7% 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. The results show that only a small set of analysts, those who are geographically close to the dominant and non-dominant firms, seem to exploit the information to improve forecast accuracy.

Overall, the results in this paper provide a fuller picture of how companies affect each other beyond the explicit intra-sector connections. Moreover, using this information one can have a better understanding of the possible public information that different groups of agents overlook, which subsequently results in mis-pricing in the market. Given the economic impact of dominant firms on the national and local economies, and also the direct effects of these firms on the local businesses, they can be a useful source of information for equity analysts as well as for investors when evaluating companies' fundamentals.

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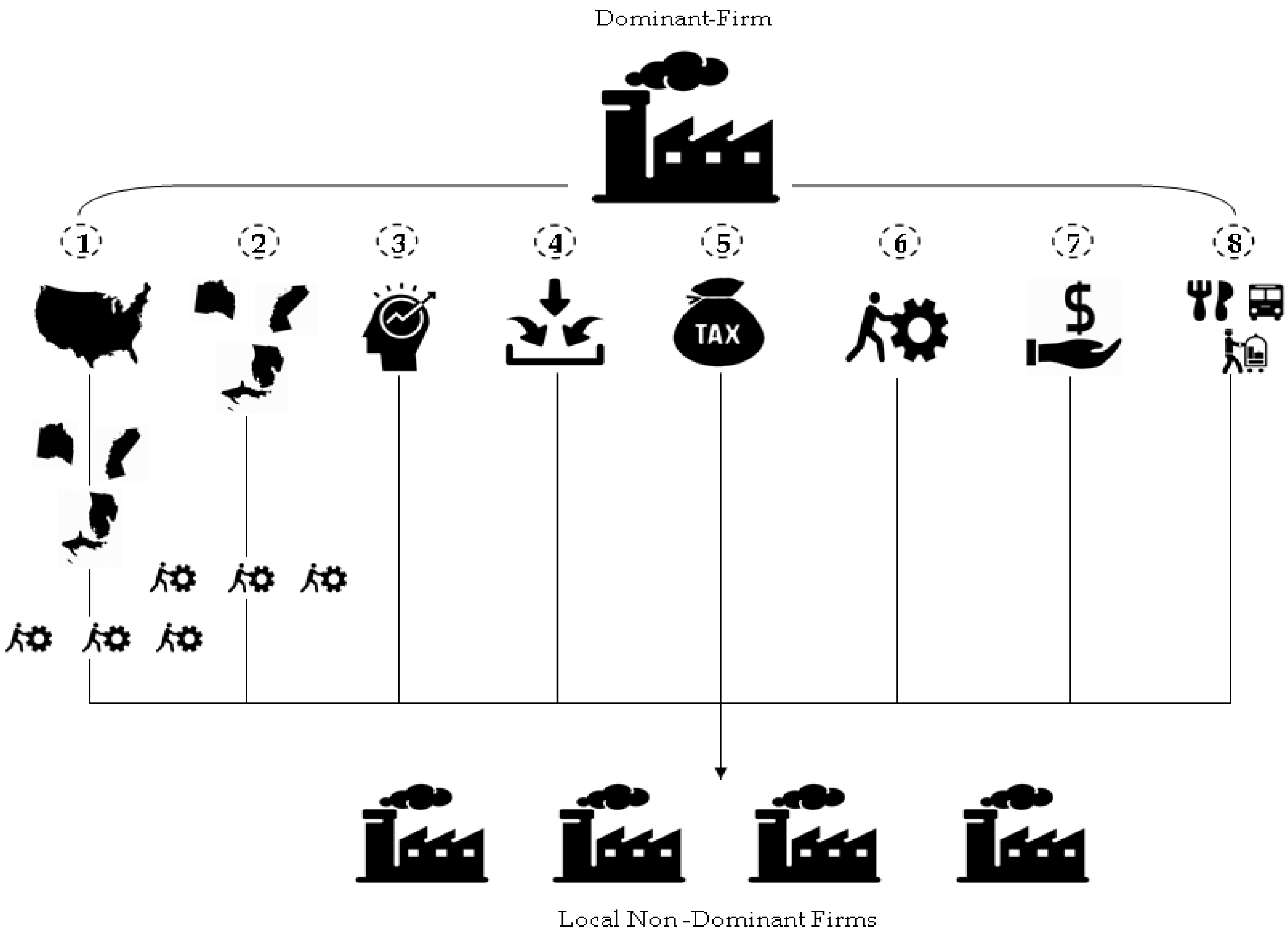
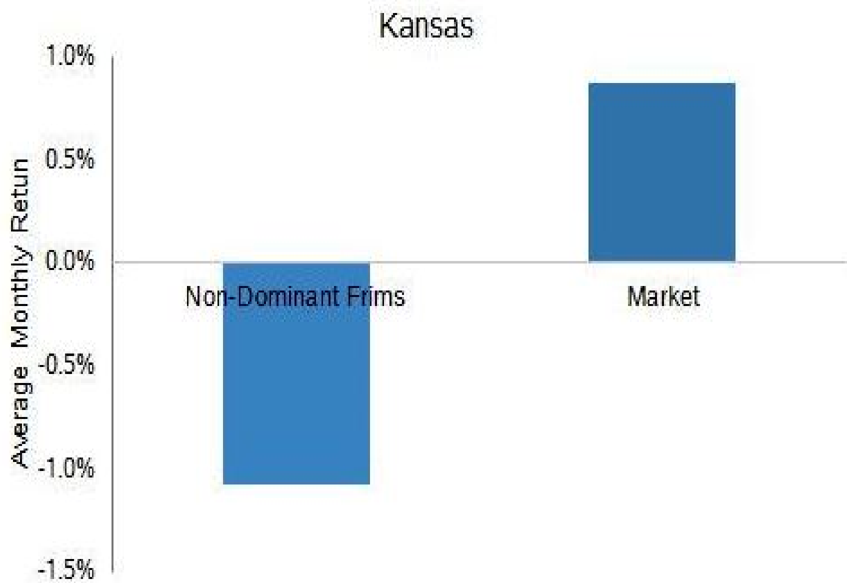


Figure 1: **Economic Channels of Shock Spillover from Dominant to Non-Dominant Firms**
This figure shows the implicit mechanisms through which dominant firms' shocks propagate to (out-of-sectors) local non-dominant companies. Channel (1) shows the effects that top 100 firms have on the U.S. business cycle (documented in Gabaix (2011)). Channel (2) shows the impact of dominant firms on their HQ states' economic fluctuations. Channel (3) shows dominant firms "Entrepreneurship Activities." Channel (4) shows the "Sectoral Connections" linkages. Channel (5) shows the "Tax Revenue." Channel (6) shows the "Employment Growth." Channel (7) shows the "Community Spending." Channel (8) shows the "Synergy Activities." See Appendix B.1 for illustrative examples for each channel.

Figure 2: **Geographic Distribution of Dominant Firms**

This figure shows the geographic distribution of dominant firms across different states. Firm information is from Compustat. The sample period is from 1995-2015.



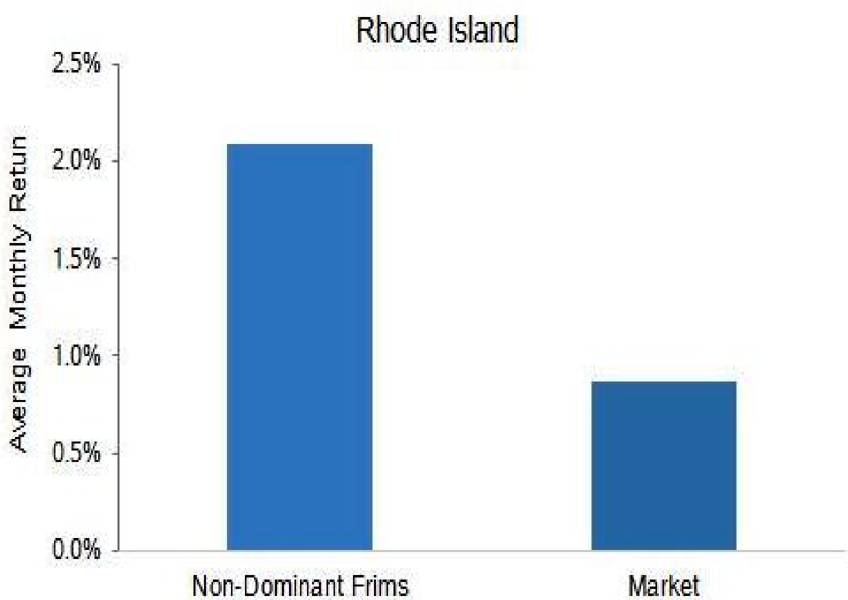


Figure 3: **Geographic Effects of Dominant Firms– Example**
This figure shows the geographic effects of dominant firms' shocks in a random year (2005) in two random states (Kansas and Rhode Island). In 2005, a Kansas dominant firm, Sprint, experienced a negative shock following a failed merger experience that the company had with Nextel. In the same year, a Rhode Island dominant firm, Textron, experienced a positive shock following a considerable shift in its product demands. This figure compares the average monthly return of non-dominant firms headquartered in the two states with the market return over 2005 and 2006. The sample of non-dominant firms are companies that do not share the same industry with the local dominant firms. Specifically, the non-dominant firms in KS are not in the Communication industry and those in RI, are not in the Aircraft industry. Firms' information is from Compustat and CRSP. Detailed information about the dominant firms' events is provided in Appendix **??**.

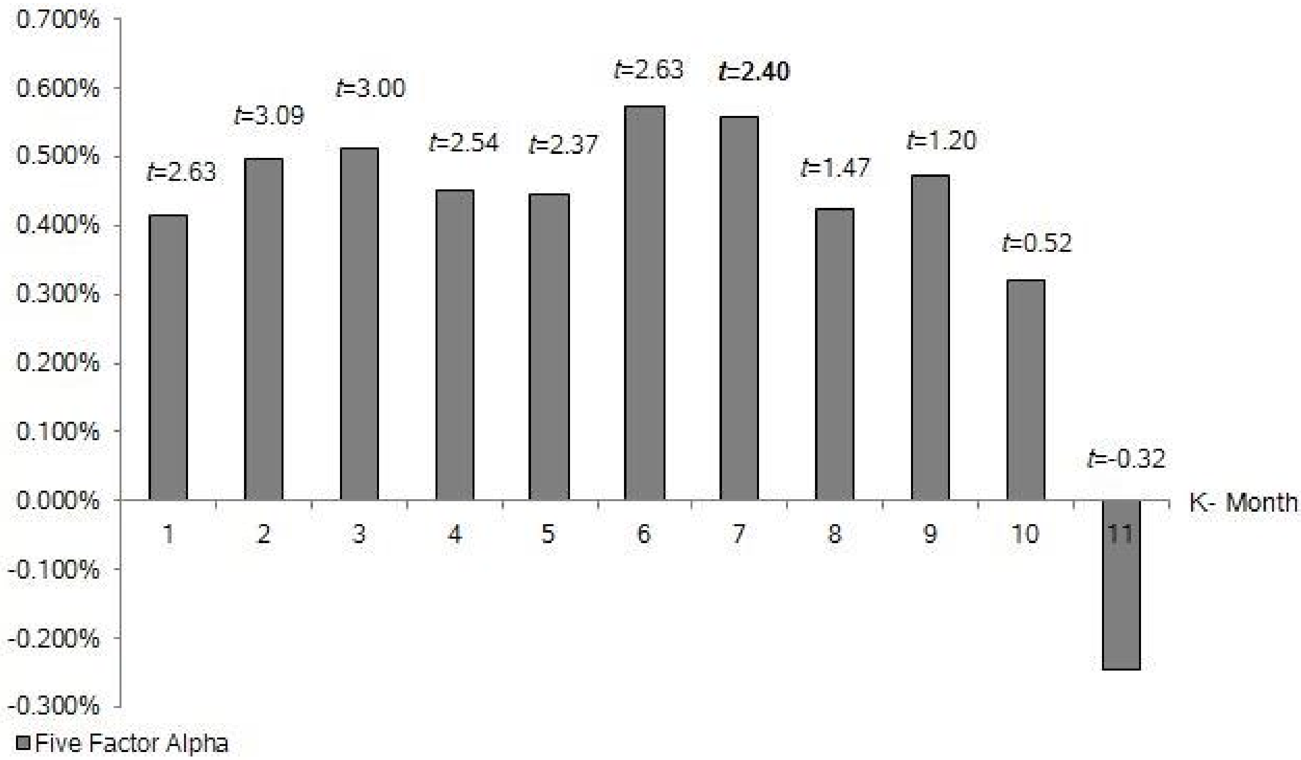


Figure 4: **Long-Short Portfolio Performance**

This figure shows the long-short performance (i.e. alpha) K month after forming the portfolio. Each year, I sort U.S. states into deciles based on the weighted average of dominant firms productivity shocks (Equation 18). Based on the information of the prior year, I create a zero-cost portfolio that longs non-dominant firms in the states of the 10^{th} decile, and shorts non-dominant firms headquartered in the states of the 1^{st} 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. Stocks' monthly returns are from the CRSP. The sample period is from July 1996 to December 2015. The t-statistics are shown below the alphas, and are based on standard errors that are clustered at year and month level.

Table 1: **Summary Statistics**

This table presents the summary statistics of the main variables used in the empirical analysis. Panel A and B show the summary statistics for the dominant and non-dominant firms respectively. Panel C reports the Pearson rank correlations, where ** represents significance at the 5% level. Dominant firms are the U.S. top 100 largest firms defined based on the firm's prior year net sales. *Firm's specific shocks* are the difference between the firm's and the average of other firms' productivity growth (Equation 8). *Market-to-Book* 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 one when operating income (dividend) is negative, and zero otherwise. *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* is $State\ Tax = \frac{Income\ State\ Tax}{Total\ Income\ Tax} \times Total\ Tax\ Paid$. The detail sources of each variable are reported in Table A1. The sample period is from 1995 to 2015.

Panel A: Dominant Firms						
Main Variables	Mean	P25	P50	P75	Std.	# Obs.
Firm Productivity Shocks (%)	0.000	-3.943	-0.243	4.235	12.330	2,100
Market-to-Book	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
Panel B: Non-Dominant Firms						
Firm Productivity Shocks (%)	0.000	-10.139	-0.600	9.222	44.412	55,333
Market-to-Book	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

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 Productivity Shocks**
This table shows the propagation of dominant firms' productivity shocks to non-dominant firms in the same local area. Specifically, this table tests the following Fama and Macbeth (1973) regression: *Non-Dominant Shocks*$_{t+1}$ $= \alpha + \beta_1$ *Dominant-Firm's Shocks*$_t$ $+\beta X_t + \varepsilon_{t+1}$. Column 1 shows the estimates with the sample of non-dominant companies that are headquartered in the same state as dominant firms. Column 2 shows the estimation results for the sample of non-dominant firms that share the same industry and headquarter state with dominant firms. Column 3 shows the regression results for the sample of non-dominant firms that are headquartered in the same state as dominant firms but operate in a different industry. GDP information is from the BEA. The sample period is from 1995-2015. All 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 (1987) method.

Dependent Variable: Non-Dominant Firm's Productivity Shocks (*t+1*)			
	(1)	(2)	(3)
Dominant Firm	**0.0049**	**0.0202**	**0.0033**
Productivity Shocks (t)	**(2.46)**	**(2.02)**	**(2.26)**
Non-dominant Firm	-0.1982	-0.1216	-0.2017
Productivity Shocks (t)	(-3.50)	(-2.94)	(-3.63)
Cash Flow (t)	-0.0017	0.0183	-0.0032
	(-0.31)	(2.46)	(-0.61)
Leverage (t)	0.0245	0.0386	0.0238
	(6.83)	(5.05)	(6.25)
Dividend Yield (t)	-0.3125	-0.1124	-0.3239
	(-1.24)	(-1.73)	(-1.22)
Market-to-Book (t)	0.0077	0.0262	0.0069
	(2.13)	(2.70)	(1.92)
Loss (t)	0.0272	0.0757	0.0245
	(2.55)	(5.82)	(2.29)
Size (t)	-0.0307	-0.0805	-0.0284
	(-3.08)	(-5.49)	(-2.85)
Constant	-0.0170	-0.0275	-0.0161
	(-0.75)	(-1.71)	(-0.69)
# Obs.	251,918	16,150	235,768
Average R^2	0.11	0.11	0.11

Table 3: **Geographic Spillover of Shocks to Out-of-Sector Firms**
This table reports evidence that the documented shock spillover in Table 2 is over and above direct/intra-sector connections between dominant and non-dominant firms. Column 1 shows the analysis using the TNIC industry classification. Specifically, Column 1 shows Fama and Macbeth (1973) regressions where I exclude any pairs of dominant and non-dominant firms that have a positive similarity in their product markets. Column 2 shows the estimates that exclude firm pairs that have customer-supplier links. Column 3 excludes dominant firms that work in industries with more than 80% out-of-sector supplier-customer connections (i.e. service industries). Firm data are from Compustat. GDP information is from the BEA. Firms' customer-supplier connections are from Cohen and Frazzini (2008). TNIC data are from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). The sample period is from 1995-2015. All 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 (1987) method.

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

Table 4: **Alternative Economic Channel: State Income Taxes**

This table shows the impact of dominant firms' state income tax payments on geographic spillovers. Specifically, this table reports the estimation results for the following regression: $\textit{Non-Dominant Shocks}_{t+1} = \alpha + \beta_1\, \textit{Dominant-Firm's Shocks}_t + \beta_2\, \textit{State Tax}_t + \beta_3\, \textit{State Tax}_t \times \textit{Dominant-Firm's Shocks}_t + \beta X_t + \varepsilon_{t+1}$, where *State Tax* is: $\frac{\textit{Total Tax Paid}}{\textit{Total Income Tax}} \times \textit{Income State Tax}$. In Column 4, I additionally adjust the state tax payments by the total amount of corporate taxes in the state. The sample used in this table is dominant and non-dominant pairs that are headquartered in the same state, but operate in different industries. Firm data are from Compustat. GDP information is from the BEA. The sample period is from 1995-2015. All 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 (1987) method.

Dependent Variable: Non-Dominant Firm Productivity Shocks (t+1)				
	(1)	(2)	(3)	(4)
Dominant Firm	0.0034	0.0030	0.0056	0.0047
Productivity Shocks (t)	(2.13)	(2.00)	(3.90)	(2.33)
State Tax (t)		-0.0008	-0.0009	0.0029
		(-0.86)	(-1.43)	(1.36)
State Tax × Dominant Firm			**0.0074**	**0.0130**
Productivity Shocks (t)			**(2.23)**	**(2.06)**
Firm Controls	Yes	Yes	Yes	Yes
# Obs.	195,574	195,574	195,574	195,574
Average R^2	0.12	0.12	0.12	0.12

Table 5: **Economic Significance of Geographic Spillovers**

This table shows the effects of a firm's productivity shocks on the firm's earnings, sales, and cash flows. Specifically, this table tests the following regression:
$\textit{Non-Dominant Earnings}_t = \alpha + \beta_1 \textit{ Non-Dominant Shocks}_t + \beta X_{t-1} + \varepsilon_t$. Column 1 shows the Fama and Macbeth (1973) regression on the effects of non-dominant firm's shocks on the firm's earnings. Columns 2 and 3 repeat the above regression, using a non-dominant firm sales or cash flows as the dependent variable. Firms data are from Compustat. GDP information is from the BEA. The sample period is from 1995-2015. All 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 (1987) method.

	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)
# Obs.	47,879	47,879	47,879
Average R^2	0.48	0.51	0.41

Table 6: **Robustness Checks and Alterantive Explanations**

This table shows additional robustness checks for the main results. Column 1 shows the regression results with the weighted average of dominant firms' shocks as the main independent variable (Equation 18). Column 2 shows the results, using TNIC to identify firms' industries. Column 3 shows the regression results that adjust shocks to common-industry shocks (Equation 20). Column 4 shows the regression results that adjust shocks to common-local shocks (Equation 21). Column 5 restricts the sample to states with (maximum) four dominant firms. Column 6 shows the estimates excluding states with a high agglomeration of dominant firms. Column 7 shows the estimates that restrict the sample to dominant and non-dominant firms that the highest economic presence in their headquarter states. Column 8 shows the estimates using TFP as a measure of firms' productivity. Firm data are from Compustat. GDP information is from the BEA. Firms' customer-supplier data are from Cohen and Frazzini (2008). TNIC data are from Hoberg and Phillips (2010) and Hoberg and Phillips (2016). Firms' citation share data is from Bernile et al. (2016). Firm-level TFP data is from İmrohoroğlu and Tüzel (2014). The sample period is from 1995-2015 in Columns 1-6. The sample period is from 1995-2011 in Columns 7. The Sample period is from 1995-2009 in Column 8. All 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 (1987) method.

	Independent Variable Non-Dominant Firm's Productivity Shocks (*t+1*)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Average of Dominant Firms Shocks (t)	**0.0324**							
	(2.29)							
Dominant Firm Productivity Shocks (t)		**0.0033**	**0.0057**	**0.0084**	**0.0203**	**0.0073**	**0.0069**	**0.0033**
		(2.26)	**(2.05)**	**(4.62)**	**(2.07)**	**(2.15)**	**(3.18)**	**(2.35)**
Non-Dominant Firm Productivity Shocks (t)	-0.1886	-0.2015	-0.1912	-0.1891	-0.1977	-0.1801	-0.1444	-0.2972
	(-5.58)	(-3.63)	(-3.94)	(-3.30)	(-9.80)	(-3.71)	(-2.48)	(-5.52)
Cash Flow (t)	0.0025	-0.0032	-0.0059	-0.0049	0.0109	0.0004	-0.0018	-0.0259
	(0.77)	(-0.61)	(-0.92)	(-0.85)	(1.60)	(0.11)	(-0.50)	(-6.38)
Leverage (t)	0.0255	0.0238	0.0221	0.0243	0.0081	0.0317	0.0401	0.0281
	(6.89)	(6.25)	(4.58)	(5.63)	(0.79)	(5.16)	(5.26)	(7.33)
Dividend Yield (t)	-0.1293	-0.3239	-0.3606	-0.3275	-0.0189	-0.0656	-0.0281	-0.2402
	(-1.40)	(-1.22)	(-1.23)	(-1.23)	(-0.51)	(-2.17)	(-0.50)	(-1.90)
Market-to-Book (t)	0.0098	0.0069	0.0018	0.0062	0.0098	0.0102	0.0104	0.0162
	(1.62)	(1.92)	(0.52)	(2.40)	(2.69)	(1.31)	(1.55)	(3.81)
Loss (t)	0.0353	0.0245	0.0219	0.0244	0.0366	0.0394	0.0185	0.0111
	(3.26)	(2.29)	(2.16)	(2.35)	(1.65)	(2.29)	(1.94)	(0.48)
Size (t)	-0.0430	-0.0284	-0.0148	-0.0193	-0.0643	-0.0441	-0.0516	-0.0562
	(-3.55)	(-2.85)	(-1.71)	(-1.62)	(-2.92)	(-2.91)	(-4.23)	(-2.43)
Constant	-0.0185	-0.0161	-0.0187	-0.0161	-0.0152	-0.0077	0.0061	-0.0013
	(-0.90)	(-0.69)	(-0.74)	(-0.78)	(-0.53)	(-0.41)	(0.35)	(-0.05)
# Obs.	42,417	235,768	235,768	235,767	5,285	67,613	80,061	127,906
Average R^2	0.09	0.12	0.11	0.12	0.14	0.08	0.13	0.14

Table 7: **Geographic Spillovers and Predictable Returns**
This table examines the market understanding of the effects that dominant firms' shocks have on non-dominant firms. Each year, I sort U.S. states into deciles based on the weighted average of dominant firms productivity shocks (Equation 18). Based on the information of the prior year (i.e. year $t-1$), I create a zero-cost portfolio that longs non-dominant firms in the states of the 10^{th} decile, and shorts non-dominant firms headquartered in the states of the 1^{st} decile. Following Fama and French (1993), portfolios' return are calculated from July of year t to June of $t+1$, and the portfolios 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 (SD), 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 includes non-dominant firms that share the same HQ state as 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 (1993) three-factor, the Carhart (1997) momentum factor, and Pastor and Stambaugh (2003) liquidity factor. Stocks' 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 year and month level.

Panel A: All Local Non-Dominant Firms					
Decile	Average of Monthly Excess Return-EW (%)	SD (%)	Sharpe Ratio(%)	Market Share (%)	State (%)
Long-Short	**0.44**	**2.68**	**16.37**	**32.01**	**18.78**
1 (Short)	0.79	6.88	11.53	16.01	7.51
2	0.79	6.91	11.45	14.25	10.74
3	1.09	6.50	16.74	7.26	10.08
4	0.99	6.91	14.31	0.06	9.70
5	1.09	6.85	15.85	6.98	10.47
6	0.71	7.38	9.59	5.06	8.87
7	0.99	6.51	15.23	7.63	8.91
8	0.55	6.92	8.00	10.08	10.39
9	1.03	7.04	14.59	10.12	10.34
10 (Long)	1.23	6.68	18.44	16.00	11.27

Panel B: All Local Non-Dominant Firms–Equally Weighted Portfolio				
	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 Portfolio				
	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 Portfolio				
	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 Portfolio				
	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: **Analysts and Dominant Firms**

This table examines whether equity analysts incorporate the information contained in dominant firms' shocks. Specifically, this table shows the estimates for the following regression: $Forecast\ Errors_{a,t} = \alpha + \beta_1\ Dominant\text{-}Firm_{t-1} + \beta_2 Shocks_{t-1} + \beta_3\ Dominant\text{-}Firm \times Shocks_{t-1} + \beta X_i + \delta Z_a + \varepsilon_{a,t}$. Column 1 shows the impact of productivity shocks on analysts' earnings forecast errors. Columns 2 and 3 show the results with analysts' accuracy and forecast age as the dependent variable. Stock information is from CRSP and Compustat. GDP information is from the BEA. Analysts' earnings forecasts are from I/B/E/S. All-star information is from Huang et al. (2014). Analyst location is from Antoniou et al. (2016). The sample period is from 1995-2015. All 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 (1987) method.

	Dependent Variable:		
	Forecast Errors	Accuracy	Forecast Age
	(1)	(2)	(3)
Dominant Firm	**0.0697**	**0.1539**	**0.0582**
	(4.08)	**(6.13)**	**(1.12)**
Productivity Shocks	-0.0129	-0.0090	-0.0023
	(-1.54)	(-1.11)	(-0.30)
Dominant Firm ×	0.0151	0.0118	-0.0108
Productivity Shocks	(2.35)	(1.34)	(-1.41)
Brokerage Size	-0.0354	-0.0323	-0.0407
	(-9.22)	(-2.25)	(-4.93)
All-Star	0.0260	0.0334	-0.0629
	(0.88)	(1.45)	(-5.31)
Local Analyst	0.0165	0.0347	0.0221
	(1.05)	(3.75)	(2.82)
Experience	0.0269	0.0163	0.0185
	(4.79)	(1.87)	(1.67)
Constant	-0.1651	-0.2119	-0.0241
	(-3.17)	(-5.62)	(-0.37)
Firm Controls	Yes	Yes	Yes
# Obs.	115,159	115,159	115,159
Average R^2	0.11	0.32	0.10

Table 9: **Analysts and Geographic Networks**

This table examines equity analysts' understanding of geographic spillovers. Specifically, this table reports the Fama and Macbeth (1973) regression results for the following regression: $Forecast\ Errors_{a,i,t} = \alpha + \beta_1\ Dominant\text{-}Firm\text{'}s\ Shocks_{j,t-1} + \gamma X_i + \delta Z_a + \varepsilon_{a,i,t}$. The dependent variable is the analysts' quarterly forecasts error for the non-dominant firms that are headquartered in the same state as dominant firms. Columns 1 to 3 show the results using the sample of all local non-dominant firms. Columns 4 to 6 repeat the same analyses as in the first 3 columns with the sample of out-of-sector non-dominant firms. Column 7 to 9 report the regression estimates with the analyst accuracy as the dependent variable. Stock information is from CRSP and Compustat. GDP information is from the BEA. Analysts' earnings forecasts are from I/B/E/S. All-star information is from Huang et al. (2014). Analyst location is from Antoniou et al. (2016). The sample period is from 1995-2015. All 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 (1987) method.

	Forecast Errors			Forecast Errors			Accuracy		
	Panel A: All Local Non-Dominant Firms			Panel B: Out-of-Sector Non-Dominant Firms			Panel C: Out-of-Sector Non-Dominant Firms		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dominant Firm Productivity Shocks	**0.0151**			**-0.0013**			**0.0007**		
	(3.68)			**(-0.35)**			**(0.18)**		
Dominant Firm Positive Productivity Shocks		**0.0052**			**-0.0014**			**0.0021**	
		(1.48)			**(-0.39)**			**(0.40)**	
Dominant Firm Negative Productivity Shocks			**0.0107**			**0.0052**			**0.0016**
			(2.62)			**(1.09)**			**(0.26)**
Brokerage Size	-0.0144	-0.0186	-0.0110	-0.0165	-0.0210	-0.0138	-0.0088	-0.0123	-0.0069
	(-2.40)	(-2.54)	(-1.54)	(-2.07)	(-2.12)	(-1.77)	(-0.44)	(-0.50)	(-0.43)
Both-cover	-0.0191	0.0263	-0.0410	-0.0251	-0.0142	-0.0233	0.0633	0.1861	0.0226
	(-0.57)	(0.90)	(-0.93)	(-0.36)	(-0.20)	(-0.27)	(0.96)	(3.77)	(0.27)
All-Star	0.0416	0.0401	0.0406	0.0083	-0.0000	0.0186	0.0572	0.0576	0.0563
	(1.08)	(1.08)	(1.05)	(0.36)	(-0.00)	(0.61)	(2.34)	(2.22)	(2.67)
Local Analyst	-0.0005	0.0062	-0.0039	-0.0324	-0.0150	-0.0402	**-0.0577**	**-0.0392**	**-0.0561**
	(-0.02)	(0.18)	(-0.13)	(-1.25)	(-0.59)	(-1.55)	**(-4.86)**	**(-2.64)**	**(-3.65)**
Experience	-0.0272	-0.0207	-0.0358	-0.0039	-0.0081	-0.0079	-0.0295	-0.0335	-0.0299
	(-1.44)	(-1.07)	(-1.80)	(-0.25)	(-0.41)	(-0.51)	(-1.44)	(-1.27)	(-1.69)
Constant	0.6607	0.5952	0.7162	0.7968	0.7092	0.8665	1.8901	1.8180	1.9522
	(9.39)	(9.61)	(9.15)	(13.77)	(17.21)	(13.35)	(8.91)	(9.70)	(8.59)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	612,969	286,122	326,847	340,412	164,437	175,975	340,412	164,437	175,975
Average R^2	0.03	0.03	0.04	0.05	0.05	0.05	0.23	0.23	0.24

Appendices

to accompany

Idiosyncratic Shocks, Geographic Spillovers, and Asset Prices

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.

A Variable Definition

Table A1: **Definition and Sources of Main Variables**
This table defines the main variables used in the empirical analyses. The main data sources are: (i) CRSP: Center for Research on Security Prices, (ii) CCM: Annual CRSP-COMPUSTAT Merged Database, (iii) I/B/E/S: Institutional Brokers Estimate System from Thomson Financial, and (iv) BEA: Bureau of Economic Analysis.

Variables Name	**Description**	**Source**
All-Star Dummy	Set to one if an analyst is ranked among II All Americans list in the previous year	I/B/E/S, Huang et al. (2014)
Firm Size	Natural logarithm of total assets	CCM
High IO Dummy	Set to one, if a non-dominant firm's industry receives more than 5% of its total inputs from a dominant firm's sector	CCM, BEA
Leverage	Sum of short-term and long-term debt, divided by total asset	CCM
Loss Dummy	Set to one if operating income is negative, zero otherwise	CCM
Market-to-Book	Sum of market equity, short term debt, long term debt, divided by total asset	CCM
Dividend Yield	Dividend divided by shareholders' equities	CCM
Earnings	Operating income after depreciation divided by total asset	CCM
Cash Flows	Cash flows from operating activities divided by total assets	CCM
Dominant Firm Dummy	Set to one, if the company is among the top 100 largest U.S. firms	CCM

Table A1: **Definition and Sources of Main Variables – (cont'd)**

Experience Dummy	Set to one if an analyst has more than three years of experience in the dataset	I/B/E/S
Forecast Age	Number of days between an analyst's most recent forecast and company's actual announcement	I/B/E/S
Forecast Errors	(Analyst Forecast - Actual Earnings)/Price, where Price is the stock price two days before the forecast date	I/B/E/S, CRSP
Industry Category	Fama-French 48 portfolio industries	K. French's Website
Local Analyst Dummy	Set to one if an analyst's brokerage is located in the same state as the firm that the analyst covers	I/B/E/S, Antoniou et al. (2016)
Number of Employees	Total number of employees working in a specific firm	CCM
State Tax	(Income State Tax/ Total Income Tax) $\times$ Total Tax Paid	CCM

B Productivity Shocks and Economic Links

This appendix provides illustrative examples for the economic effects of dominant firms and further shows examples about their productivity shocks.

B.1 Dominant Firms' Economic Effects–Examples

This section, provides detail examples for the implicit economic channels presented in Figure 1.

B.1.1 Charitable Activities

An example for this case is Textron, headquartered in Rhode Island. Textron is a leading company in its industry, avionics, responsible for more than $13 billion of the industry's revenue in 2015. The company is widely involved in charitable works and supports local businesses located in RI. This financial support is mainly funded through the company's "Charity Trust Fund." Many firms, outside the aircraft industry, benefit from these activities. For example, in 2006, through the "Grant Program," Textron donated more than $400,000 to different local businesses, including the International Institute of RI.

Another example for the local donations of large companies, is Coca-Cola, headquartered in Georgia. According to the company's website in 2014, the "chairman and CEO announced a $1 million grant to the Community Foundation of Greater Atlanta. This grant supports the City of Atlanta's Centers of Hope program and helps it expand from two locations to all 10 City of Atlanta recreation centers. These centers provides fitness, health and wellness and nutrition activities to more people in more places."

B.1.2 Entrepreneurship Activities

One example for this channel is Sprint incorporation, headquartered in Kansas city. The company is widely involved in entrepreneurship activities, supporting local business in KS, that are not necessarily in a direct relationship with Sprint.

B.1.3 Providing Job Opportunities

According to the Nashville Health Care Council report in 2015, for every direct 1,000 jobs in the Nashville health care industry, more than 500 jobs is created in other industries such as retail trade, accommodation industry, finance, etc. Given that a dominant firm in the Nashville (such as HCA Healthcare) accounts for more than 50% of the revenue in Nashville's health care industry, one can see the considerable impact that a dominant company can have on other local firms, even in the absence of intra-sector connections.

Another example for this case is Qualcomm, headquartered in California. According to the company's annual reports "adding 1,000 direct jobs in the company may result in generating approximately 500 indirect jobs, $26.72 million in indirect payroll, and $75.97 million of indirect economic output. Qualcomm's presence in the region supports 27,365 jobs paying an average annual wage of more than $70,000."

B.1.4 Synergy Activities

Synergy occurs when a company recirculates, repackages and redeploys an intellectual property that it already owns. These activities have considerable byproducts that can affect other industries. An example of this situation is Disney's synergy activities on creating the hockey team of "Mighty Ducks." That activity had a huge economic impact on California and specifically on Disney's headquartered city, Anaheim. Each year, visitors spend considerable amount of money to visit the city which creates different jobs in various sectors, such as transportation, food industry, etc.

Another example is the economic impact that Sacramento gains from the Amgen tour of California. The estimated economic impact for the 2017 was close to $4 million, which mainly comes from riders and fans usage of hotels, restaurants and other miscellaneous purchases.

Table B1: **Firms' Specific Shock: Examples**

This table compares the estimated firm-specific shocks (both positive and negative) 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. Specifically, firm's specific shocks are equal to: $\widehat{\xi_{j,t}} = g_{j,t} - \bar{g}_t$ (Equation 8). Firms data are from Compustat. GDP information is from the BEA. Information on the firm's specific events are from the company's 10-K and 8-K filings, available on the SEC.

HQ State	Dominant Firm	Year	Event	Estimated Productivity Shock
NY	Colgate-Palmolive	2015	Delay in achieving expected benefits from the 2012 "Restructuring Program"	-6.2%
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 global 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%
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%
WI	Rockwell Automation	1996	Sales from Rockwell's continuing businesses in 1996 were up 14% led by significant increases in the Automation, Semiconductor Systems and Automotive's Light Vehicle Systems businesses	8.4%

C Dominant Firms' Impact on Their HQ States

In this appendix, I study whether productivity shocks to dominant firms explain the GDP growth of their headquarter states. To do so, each year I compute the productivity shocks to dominant firms using the method explained in Section 3.2.1. Next, for each state, I calculate the weighted average of dominant firms' specific shocks as:

$$\Gamma_{s,t} = \sum_{i=1}^{K} \frac{S_{j,s,t-1}}{Y_{s,t-1}} \hat{\xi_{j,s,t}} \tag{28}$$

where K shows the total number of dominant firms in state s, at time t. Subsequently, I stud the effect of dominant firms' shocks on the GDP growth of their headquarter states, using the following regression:[31]

$$logGDP_{s,t} - logGDP_{s,t-1} = \alpha + \beta_1 \Gamma_{s,t} + \beta_2 \Gamma_{s,t-1} + \varepsilon_{s,t} \tag{29}$$

From the above regression, I am interested in the estimated R^2, which captures the economic power of Γ in explaining GDP growth (see Gabaix (2011)). Column 4 of Table C1 shows the estimated R^2 of the above regression for each state. The predictive power of dominant firms on the HQ state economic growth is large and significant. For example, productivity shocks to the only dominant firm in Nebraska (Union Pacific Railroad) explain more than 40% of the state's GDP growth. This effect is more than 80% in Idaho.

Together, this analysis shows that productivity shocks to dominant firms have substantial economic effects on the business cycles of their headquarter states. This effect subsequently impacts financial service, job labor and investment opportunities in the state which in turn influences local businesses (i.e. non-dominant firms).

[31] I follow Biswas et al. (2017) and define state-level economic growth using the annual state-level log change in the real GDP per capita.

Table C1: **Dominant Firms' Impact on Their HQ States**

This table shows the effects of productivity shocks to dominant firms 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 the following regression: $logGDP_{s,t} - logGDP_{s,t-1} = \alpha + \beta_1\Gamma_{s,t} + \beta_2\Gamma_{s,t-1} + \varepsilon_{s,t}$, where $\Gamma_{s,t}$ shows the weighted average of dominant firms' productivity shocks: $\Gamma_{s,t} = \sum_{i=1}^{K} \frac{S_{j,s,t-1}}{Y_{s,t-1}} \hat{\xi_{j,s,t}}$, $S_{j,t-1}$ and Y_{t-1} are the firm's net sales and the state's GDP in the prior year respectively. Firms' data are from Compustat. State GDP information is from the BEA. The sample period is from 1995-2015.

(1) State	(2) # Dominant Firms	(3) $\frac{\#\ DominantFirms}{\#\ AllFirms}$ (%)	(4) R^2 (%)
AR	3	10.0	14.0
AZ	1	0.8	24.0
CA	23	1.5	9.1
CO	3	1.4	63.8
CT	2	1.2	17.2
DE	1	4.5	8.1
FL	6	1.4	35.1
GA	9	4.3	35.4
ID	2	10.0	85.0
IL	25	8.7	3.7
IN	2	2.6	18.6
KS	1	5.1	32.2
LA	2	9.7	0.9
MA	7	1.5	10.9
MD	2	1.4	30.6
MI	14	10.7	30.8
MN	7	3.4	23.5
MO	7	6.5	3.3
NC	4	2.4	24.7
NE	1	3.7	43.7
NJ	13	3.4	7.9
NY	23	3.8	10.9
OH	8	3.4	3.0
PA	6	2.0	29.0
RI	2	8.7	14.7
SD	1	14.3	26.4
TN	6	5.2	18.1
TX	24	3.6	22.6
UT	1	1.3	52.4
VA	8	3.4	34.1
WA	8	5.2	1.1
WI	5	4.7	13.1

D Sectoral Connections

In this section, I study the role of sectoral connections on the geographic spillover of shocks from dominant to local non-dominant firms. Figure 2 illustrates that even a dominant and non-dominant firm are not directly connected, their sectors can have business interactions. Specifically, these implicit sectoral interactions happen when a dominant firm's industry (i.e. Industry 1 in Figure 2) provides considerable inputs to a non-dominant firm's sector (i.e. industry 3). Through this interaction, I expect to find a higher shock spillover from dominant to non-dominant companies.

To investigate the role of sectoral connections, I use the Input/Output (IO) data from the "Benchmark Use Table" available on the BEA. The BEA provides updated information every five years. Similar to the previous studies (Fan and Goyal (2006) and Menzly and Ozbas (2010)), I use the information of 1997 for the time period of 1995 to 1999; the information of 2002 for the time period of 2000 to 2005, and the information of year 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 the specification I remove all intra-sector/market links, to assure that the implicit vertical interaction does not capture the effects of explicit/direct linkages.

Table D1 provides supporting evidence for the above hypothesis. As shown in Column 3 of Table D1, all else equal, (out-of-sector) non-dominant firms that have a *High IO* connection with dominant companies, experience a higher level of shock spillover (coefficient=0.0046 t-statistic=2.19).

While sectoral connections between dominant and non-dominant firms facilitate the shock transmission, they are not the exclusive drivers of the geographic cascade effect. As shown in Table D1, the impact of dominant firms' shocks stays statistically significant in all of the specification. This result further supports the argument in section 4.5.3.

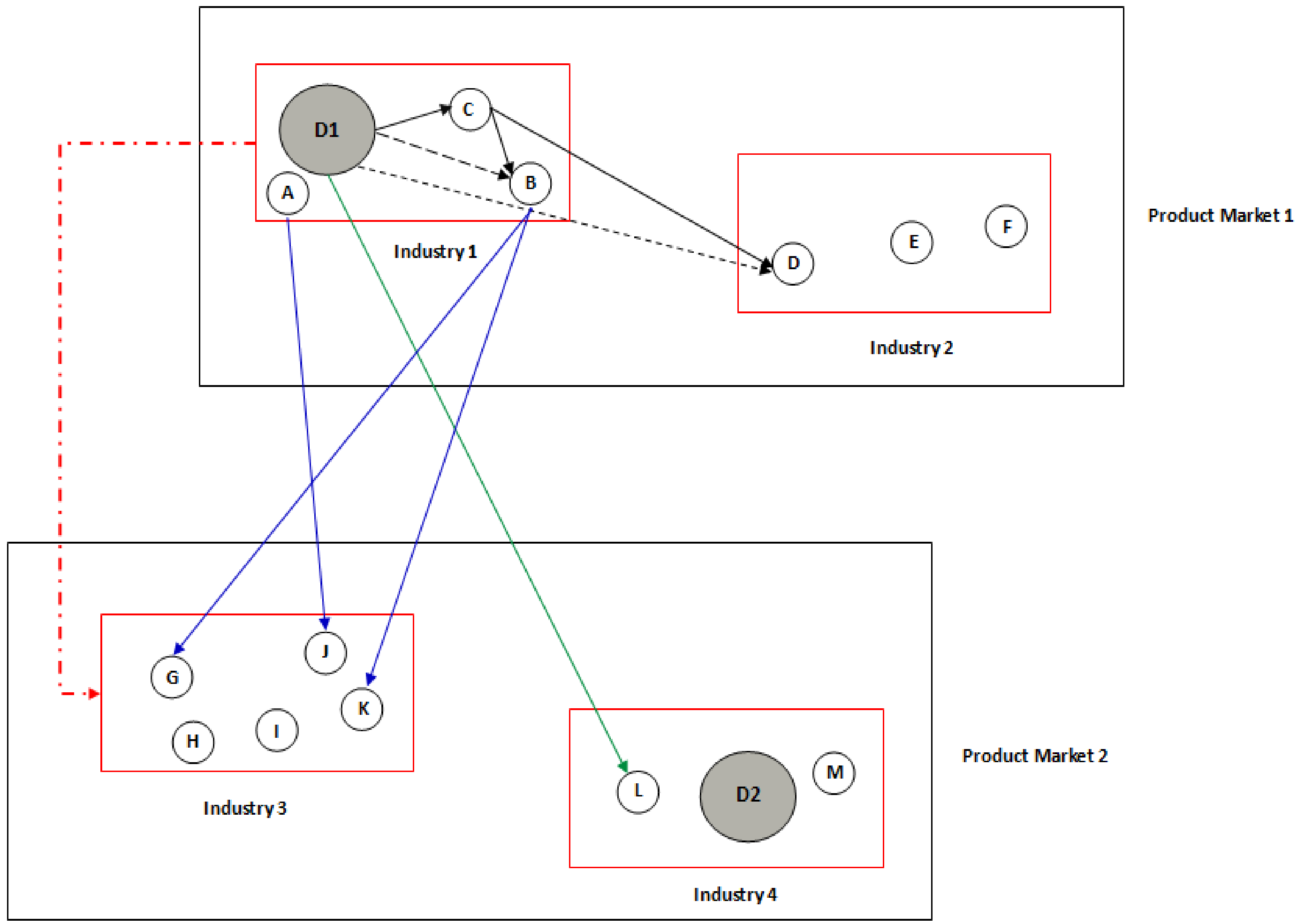


Figure D1: **Sectoral Connections**
This figure shows explicit and implicit connections between dominant and non-dominant companies. links that are shown in black, capture the explicit interactions between dominant and non-dominant firms, through intra-sector, or intra-market similarities (see Sections 4.1, and 4.2.2). Links shown in green, depict the direct out-of-sector linkages through the customer-supplier interactions (see Section 4.2.3). Dashed-red lines show the sectoral connections, even when firms are not directly connected. These interactions happen when despite any direct links between firms, more than 5% of the total inputs in the non-dominant firms' sector (i.e. Industry 3) is from the dominant company's sector (i.e. Industry 1).

Table D1: **Sectoral Connections**

This table shows the impact of sectoral connections (through input/output linkages) on the shock spillover from dominant to local non-dominant firms. *High IO* is a dummy variable equals one, if more than 5% of the total inputs of a non-dominant firm's industry are from a dominant firm's sector. The sample used in this table is dominant and non-dominant pairs that are headquartered in the same state. Any within-sector/within-market linkages between firms are excluded. Firm data are from Compustat. GDP information is from the BEA. Input/output data are from the Benchmark Use Table available on the BEA. The sample period is from 1995-2015. All 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 (1987) method.

	Dependent Variable: Non-Dominant Firm Productivity Shocks (t+1)		
	(1)	(2)	(3)
Dominant Firm	**0.0052**	**0.0067**	**0.0062**
Productivity Shocks (t)	**(2.01)**	**(2.85)**	**(2.65)**
High IO (t)		0.0207	0.0262
		(1.42)	(1.73)
High IO×Dominant Firm			**0.0046**
Productivity Shocks (t)			**(2.19)**
Firm Controls	Yes	Yes	Yes
# Obs.	127,167	127,167	127,167
Average R^2	0.13	0.13	0.13