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Geography of Firms and Propagation of Local Economic Shocks

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JEL Classification: C23, E32, E37, G10.

Keywords: Local business cycles, geographical networks, economic links, publicly-traded firms, propagation of recessions.

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Geography of Firms and Propagation of Local Economic Shocks

Abstract – This study shows that the geographical distribution of publicly-traded firms generates an economic network that links the economic environments of all U.S. states. Using a novel measure of economic linkages among publicly-traded firms, we build a state-level network of economic connections and show that local economic shocks propagate through this geographical network. Specifically, for each state, we identify U.S. states that are economically relevant for firms headquartered in that state and show that economic conditions in economically relevant states predict the economic environment in the headquarter state. These results do not merely reflect the impact of omitted common national shocks. Using monetary losses from state-level natural disasters as an instrument, we show that state-level economic shocks propagate through the economic network generated by public companies. Overall, this evidence has important implications for the evaluation of targeted government policies such as the recent hurricane relief or bailout programs.

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1. Introduction

A growing literature in macroeconomics investigates whether idiosyncratic microeconomic shocks can generate aggregate macroeconomic fluctuations due to the connections existing between firms and sectors (e.g., Gabaix (2011), Atalay, Hortasu, Roberts and Syverson (2011), Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012)). In particular, Gabaix (2011) shows that the 100 largest publicly-traded firms in the U.S. account for about one-third of the fluctuations in aggregate output growth. Similarly, Atalay et al. (2011) emphasize the importance of buyer-supplier networks and firm-level economic linkages.

Another strand of literature in economics and finance shows that the economic interests of firms typically span several, often distant locations (e.g., Garcia and Norli (2012)). As a result, information about profitability and performance of publicly-traded firms is geographically distributed and often resides away from corporate headquarters (e.g., Giroud (2011), Bernile, Kumar and Sulaeman (2010)).

Motivated by these studies, we examine whether the geographical distribution of publicly-traded firms' economic interests fosters meaningful economic connections among the U.S. states. Specifically we examine whether local, i.e., state-level, economic shocks propagate across the U.S. and influence the aggregate U.S. economy. This analysis has important policy implications because it can provide the basis to evaluate aggregate spillover effects of Federal policies targeted toward specific states or sectors, like in the case of federal disaster relief or bailout programs.

One of the main contributions of our study is to empirically identify an asymmetric network of state-level economic connections starting from firm-level data.[1] Specifically, based on their financial statements, we identify the geographical distribution of economic interests of the publicly-traded firms in our sample. The super-imposition of these firm-level geographic networks of economic activity gives rise to an intricate web of economic links among U.S. states, even when those states are geographically far apart.

Our key conjecture is that local economic shocks would propagate across the U.S. states through the state-to-state network. Such predictability in economic conditions across states can arise for several reasons. First, firm profits flow through the headquarters, where major corporate decisions are determined. Therefore, economic conditions in states where the firm has a presence

[1] This is important because such asymmetries are required in theoretical models where microeconomic idiosyncratic shocks affect aggregate macroeconomic fluctuations (e.g., Acemoglu et al. (2012)).

should directly affect the firm's economic activity at the headquarters. Beyond their direct impact on the headquarters state economy, publicly-traded firms could influence the perceptions of other businesses in the region. This spillover effect can further amplify the impact of economic shocks that originate in economically connected regions.

Consider an example. Dell Computers is one of the dominant publicly-traded firms near Austin, Texas. If the demand for Dell product weakens in states where Dell has a major economic presence, Dell may announce a major layoff at its headquarters in Round Rock, Texas. This announcement can affect the local labor market and even the real-estate market in Austin if several Dell employees decide to leave Austin and search for employment opportunities elsewhere. Thus, economic conditions in far-away places have the potential to influence the economic conditions in a given state as a result of the geographical dispersion of publicly-traded firms' economic interests.

To construct the state-level network of economic connections, we use textual analysis of the annual financial statements of publicly-traded firms. For each firm, we begin by identifying the state where the firm is headquartered (i.e., the HQ state). Then, using a parsing algorithm, we search the annual 10-K reports of the firm and count the number of times each U.S. state is mentioned. The states cited in the annual reports are identified as economically relevant states or economic centers (EC). Last, we aggregate the firm-level citation measures at the HQ state-level. For each state, we average the EC citations of all firms headquartered in the state to obtain a measure of state-to-state economic connectivity.

In this network, two states have stronger economic ties when firms headquartered in the first state cite the second state more frequently in their respective 10-K reports. The state-level economic network is not symmetric since not all states are equally important (see Figure 4). As expected, we find that the most economically relevant states in the U.S. are California, New York and Texas. However, states like Florida, Illinois, Virginia, and Washington, are also important economic centers.

In our empirical tests, we embed the network-based economic proximity measure into a forecasting regression and find that the current average gross state product (GSP) growth of EC states predicts the future GSP growth of HQ states. This relation is statistically and economically significant. For example, a one percent increase in the current per capita GSP growth of New York and Illinois predicts an increase in the subsequent average per capita GSP growth of 2.10 and 1.00 percent, respectively.

Additional tests show that our baseline results are not driven exclusively by the three dominant EC states (California, New York, and Texas) and that GSP predictability is stronger when we focus on HQ states with a large sector of publicly-traded firms. Moreover, we find that predictability in GSP growth, a measure of output growth, is paralleled by predictability in production inputs growth, where the GSP growth of EC states predicts the growth in employment and investment in the HQ state. Finally, given the premise of our empirical strategy, we examine directly whether the performance of public firms is affected by local shocks in the network of EC states. We find that the future sales growth of HQ firms increases with the sales growth of EC firms as well as the GSP growth of the EC states. Overall, these results support the conjecture that the geographical distribution of publicly-traded firms' economic activities fosters the transmission of local economic shocks across the U.S. states.

Any study like ours is confronted with potential endogeneity problems. Specifically, the formation of economic linkages can be endogenous and subject to the "reflection problem" (Manski (1993)). To address this potential concern, we separate the time period used to measure economic links from the time period over which we estimate the GSP growth predictability regressions. We measure the economic links based on information from annual fillings from 1996 to 1998, while our estimation period starts in 1999.

It is also plausible that the evidence of GSP predictability is due to omitted common national shocks that affect all U.S. states. We address this concern in several ways. First, in our baseline tests, we estimate forecasting rather than contemporaneous regressions to ensure that state-level correlations due to contemporaneous national shocks are not inflating the significance of the economic links. We also include the lagged GSP growth of HQ states in the baseline specifications to absorb the effects of persistent common national shocks.

Second, for robustness, we conduct a placebo test where we randomize the connectivity between EC and HQ states. The economic conditions of the random EC states would continue to reflect common national shocks, but the transmission of local shocks should be less relevant. We find that the average GSP growth of random EC states *does not* predict the economic conditions of the HQ state, which suggests that omitted common shocks are not the main driver of our baseline results.

Last, we address the potential endogeneity using an instrumental variable (IV) method to purge the effects of common national shocks from the GSP growth of economically linked states.

Specifically, we instrument the economic conditions in EC states with the monetary losses from local natural disasters. Conceptually, monetary losses from natural disasters in EC states are a valid instrument because they affect the state-level economic growth but are not caused by a common national shock.

Confirming our baseline evidence, the IV estimation results show that past GSP growth of EC states predicts current GSP growth of HQ states.The finding that national shocks do not affect our results is not surprising; prior research has shown that aggregate shocks like inflation, wars, and federal policies are weakly related to the year-to-year fluctuations in U.S. aggregates like the GDP growth (e.g., Cochrane (1994), Gabaix (2011)).

Our study contributes to the emerging economics literature that examines how disaggregate economic conditions are related to the aggregate U.S. business cycle. In particular, Gabaix (2011) shows that idiosyncratic shocks experienced by publicly traded companies are important determinants of aggregate macroeconomic fluctuations. Motivated by this evidence, we restrict our attention to the geographical distribution of publicly-traded firms to identify the state-level network. Complementing Gabaix' findings, we demonstrate that local economic shocks propagate across the U.S. economy through the firm-level networks of economic activity. The two sets of results are intuitively related because larger firms tend to have operations across the U.S. and, thus, shocks to those firms have the potential to ripple through the network of their economic connnections.

In another related study, Conley and Dupor (2003) quantify economic proximity across sectors based on the similarity of their input-output structures. They show that sector-level networks explain productivity comovement across the sectors of the U.S. economy. Their results are consistent with Horvath (2000), who shows that sectoral shocks are important for explaining aggregate volatility. Instead of studying contemporaneous co-movements across the U.S. states, we conduct a forecasting exercise based on the dynamic spatial model of Korniotis (2010) and find evidence of economic connections that are *not* driven by industry similarities among U.S. states.

Previous theoretical work suggests specific mechanisms through which microeconomic shocks could generate macroeconomic fluctuations. For example, Durlauf (1993) develops a model in which firms interact with other local firms. We show that while physical proximity fosters connectivity between the U.S. states, even distant states are economically connected due to the links created by the geographical distribution of publicly-traded firms' activities. More recently, Acemoglu et al. (2012) develop a model of input-output linkages that results in "cascade effects", whereby shocks in one sector affect not only other sectors directly linked to it, but ultimately the whole economy. Such "cascade effects" only arise in asymmetric networks, where each sector does not rely equally on all other sectors. Our state-level network of EC linkages is asymmetric and thus similar to the "star network" of Acemoglu et al. (2012).

Our results also have important policy implications. In particular, our estimates can be used to evaluate the total economic impact of federal programs that target a specific geographical area or industry sector. Often, constituencies that benefit directly from such policies naturally support them, while those not directly affected by the programs tend to focus on their financial burden and typically ignore the potential positive spillover effects. The difficulty in passing the disaster relief package for the second costliest hurricane in U.S. history, Sandy, provides such an example. Sandy caused most of the estimated $65 billion damages in the coastal areas of New Jersey and New York, including New York City, one of the most important economic centers in the country. However, the resulting political debate focused primarily on the local benefits of intervention and ignored the potential ripple effects on other parts of the country. Similarly, by many accounts, the $5 billion TARP funds devoted to the auto industry bailout of 2008-2009 had far reaching effects beyond the immediate neighborhood of Detroit, Michigan. We show that these targeted federal programs should be evaluated on the basis of their aggregate effect on the U.S. economy, including any spillover effects on areas or sectors not directly targeted by the policy.

The rest of the paper is organized as follows. In Section 2, we describe the main data sources and the measures of economic linkages. We present our main predictability estimates in Section 3 and discuss evidence from additional tests in Section 4. In Section 5, we present evidence from various robustness tests. In Section 6, we focus on the key issue of endogeneity and present results from an instrumental variable estimation method. We conclude in Section 7 with a brief discussion.

2. Data and Proximity Measures

In this section, we provide details about our proximity measures and present the summary statistics for the main variables. We use four measures of proximity in our empirical analysis. First, we define economic proximity based on the headquarter locations of publicly-traded firms and the states where they have economic presence. We also measure proximity based on culture, physical distance, and industry composition. For each of these proximity measures, we first compute a proximity index between two states and then transform the index into scaled proximity weights. We use the scaled weights in our predictive regressions.

2.1. State-to-Firm Economic Proximity

In our main empirical analysis, we use state-to-state economic proximity indices derived from firm-level measures of economic proximity. The firm-level measure is constructed for all publicly-traded firms covered by COMPUSTAT and with available 10-K fillings on the Securities and Exchange Commission's EDGAR system.

For each firm, we first identify the state where the firm is headquartered and refer to this as the *HQ state*. Then, we count the number of times that each U.S. state is mentioned in the relevant sections of the firm's annual 10-K filing. Following Bernile et al. (2010), we refer to these states as the firm's "economic centers", *EC*. Finally, we compute the citation fraction for each firm-state pair, *CF*, by dividing the number of citations of each EC by the total number of citations across all U.S. states in the same filing. The firm-state citation fractions measure the importance of the state for the performance of the firm and provide the basis for our state-to-state measure of economic proximity.

This empirical approach is motivated by the findings in recent studies, which demonstrate that EC locations away from the HQ location are economically relevant to investors as well as managers. For instance, Bernile et al. (2010) use similar data to examine the investment decisions of institutional investors and demonstrate that value-relevant information about firm performance is available at EC locations. Using plant-level data, Giroud (2011) finds that management ability to gather information produced at non-HQ locations affects firm investment and productivity in those locations. These findings suggest that there should be a direct relation between a firm's citation fraction of a state and the importance of this EC for the performance of the firm.

2.2. State-to-State Economic Proximity

Since our main objective is to examine the aggregate implications of economic networks resulting from the geographical distribution of publicly traded firms, we aggregate the firm-state citation fractions at the HQ state-level to derive state-to-state economic proximity (EP) indices. These aggregate indices summarize the economic relevance of EC state j for firms headquartered in HQ state i. Our empirical analysis is based on the assumption that a larger citation fraction for EC state j by firms headquartered in HQ state i corresponds to a stronger link between the aggregate economic activities of states j and i.

We define two state-level indices of economic proximity. The main economic proximity index is defined as the asset value-weighted average citation fraction of state j across all firms headquartered in state i:

$$EP_{i,j}^{(1)} = \frac{1}{N} \sum_{k=1}^{N} b_{i,k} CF_{i,j,k}, \tag{1}$$

where $EP_{i,j}^{(1)}$ is the index for the HQ_i-EC_j pair, N is the number of firms headquartered in state i, $b_{i,k}$ is the book value of firm k's assets divided by the aggregate book value of assets of all firms headquartered in state i, and $CF_{i,j,k}$ is firm k's citation fraction of EC_j.

To address potential endogeneity concerns, we only compute the $EP^{(1)}$ index for the fiscal years 1996, 1997, and 1998. This allows us to separate the measurement period of the economic linkages and the estimation period of our forecasting regressions, which starts in 1999. Specifically, we use the average $EP^{(1)}$ during the three years to compute the scaled weights that we use in the estimation exercise. In robustness tests, we also consider the average values of the $EP^{(1)}$ index over the 1996 to 2008 time period.

We define the alternative index as the equal-weighted average citation fraction of state j across all firms headquartered in state i:

$$EP_{i,j}^{(2)} = \frac{1}{N} \sum_{k=1}^{N} CF_{i,j,k}, \tag{2}$$

where $EP_{i,j}^{(2)}$ is the index for the HQ_i-EC_j pair, N is the number of firms headquartered in state i, and $CF_{i,j,k}$ is firm k's citation fraction of EC_j. Similar to our main index $EP^{(1)}$, we compute the $EP^{(2)}$ index for the fiscal years 1996, 1997, and 1998. Subsequently, we use the average values of the $EP^{(2)}$ measure during the three years to compute the scaled weights that we use in the estimation exercise.

It is worth noting that the use of geographical boundaries of U.S. states to define "locations" is not the only possibility. However, various institutional reasons suggest that it may be most appropriate to focus on states as the geographical unit of analysis. To begin with, there are large differences in state-level budget rules as well as fiscal and tax policies across U.S. states. Moreover, subsidies and transfers from the U.S. Federal government are directed to U.S. states.

Therefore, state boundaries are in fact economically relevant.[2]

In contrast, more localized entities like counties or cities are limited in their power to enact policies that can have significant effects on the state economy. Further, county-level economic shocks might be too small to generate significant spillover effects on other states. For example, if a plant in a county shuts down, workers from that plant might find employment in other counties within the state. Conversely, if a shock affects the entire state (e.g., a shock to the car manufacturing industry in Detroit), then it may be more likely to affect other states. By focusing on U.S. states, we are explicitly examining the impact of large economic shocks that are local in nature, but have the potential to affect the entire U.S. economy.

2.3. Information Content of the Economic Proximity Measure

The premise of our empirical strategy is that the economy of HQ state i depends more heavily on the economy of EC state j when the performance of firms headquartered in state i is more concentrated in state j. This interpretation of the EP indices seems reasonable because they are based on state citations extracted from sections of the 10-K fillings that are related to firm performance. Specifically, following prior studies (e.g., Garcia and Norli (2012), Bernile et al. (2010)), we focus on items 1, 2, 6, and 7 of the 10-K filling.

Item 1 in Form 10-K summarizes the general development of the business of the firm, its subsidiaries, and any predecessor(s) during the prior five years, as well as the firm's industry structure and conditions. Item 2 lists the location and general character of the principal physical properties of the company and its subsidiaries. Item 6 supplies selected financial data to highlight trends in the firm's financial condition and operating performance. Finally, Item 7 includes the management's discussion and analysis (MD&A) of the company's performance. This discussion provides an account of the determinants of the firm's historical and future financial performance. Appendix A provides further details about the required content of these sections of the annual report and Appendix B provides excerpts from actual 10-K filings.

Consistent with our motivation, earlier studies show that market valuations and investors' behavior are strongly related to the geographical information contained in these sections of Form

[2] The U.S. Constitution (Article I, Section 8, Clause 3; Interstate Commerce Clause) grants the Federal government the power "to regulate commerce... among the several states...", suggesting that U.S. states and economic connections among them are a focus of U. S. institutions. Similarly, confirming the political relevance of statewide constituencies, regardless of the state's population, each U.S. state is represented by two senators who serve staggered six-year terms.

10-K (e.g., Garcia and Norli (2012), Bernile et al. (2010)). Nonetheless, inspection of the firm-level measure *vis à vis* the actual filings reveals that firm-level state citation shares may be measured with error. This is particularly the case among largest firms, which are more likely to not report a break down of the geographical distribution of their operations at the state-level. To the extent that such errors in firm-level citation shares are significant and persist following state-level aggregation, the resulting noise in the economic proximity measure would reduce our ability to establish the effect of state-to-state economic links, even if such effect exists.

2.4. Validation Tests and Economic Proximity Measure

Before proceeding with our main analysis, we directly examine whether the state-to-firm proximity indeed reflects how significant a location is on firm performance. Specifically, we perform several validation tests to show that the firm-state citation fractions capture the geographic dispersion of a firms economic interests. The economic rationale behind these tests is that firms that share economically relevant locations are more likely to face common local economic shocks as well as directly engage in a common set of transactions. As a result, there should be a common local component in their stock returns as well as in their operating performance and capital investments. For example, if a California-based firm like Adobe Systems has major economic interests in Utah, its stock returns and corporate performance should be correlated with the returns and performance of other firms that are headquartered in Utah.

To perform these validation tests, for each state, we form three mutually exclusive portfolios. The first portfolio contains all firms headquartered in the state (HQ). The second portfolio consists of firms that are not headquartered but have significant economic interests in the state, i.e., the state ranks among the top three most cited in the firm 10-K filing (EC). The third portfolio contains all firms that are neither headquartered nor have significant significant economic interests in the state ($No\ HQ/EC$). Next, we create state-level indexes by either value-weighting (VW) or citation share-weighting (SW) the firms in each portfolio. Finally, for each state, we estimate time-series models that relate the portfolio indexes of firms not headquartered in the state, EC and $No\ HQ/EC$, to the headquarters portfolio index. Appendix Table A.1 reports cross-sectional means of these regression estimates. The portfolio indexes are based on three alternative firm-level measures: (i) raw monthly stock returns (see Columns (1) to (3)), (ii) quarterly sales divided by firm assets at the beginning of the quarter (see Columns (4) to (6)), and (iii) quarterly capital expenditures divided by firm assets at the beginning of the quarter (see Columns (7) to (9)).

Focusing on the monthly equity return models, we find that the stock performance of *EC* firms is significantly related to the returns of firms headquartered in the state (see Column (1)). Further, this relation is stronger when the portfolio weights are based on firm-state citation fractions, i.e., we assign greater weight to firms that are "more local" as they cite the state relatively more frequently (see Column (3)). In contrast, the stock returns of *No HQ/EC* firms are not directly related to the returns of firms headquartered in the state (see Column (2)). Although the point estimates are negative and statistically significant, the economic magnitude of the effect is essentially zero.[3]

To examine whether comovement in stock returns reflects cash-flows or discount rates correlations, we re-estimate the state-level time-series regression models using in turn quarterly sales or capital expenditures as the dependent variable. Consistent with the results from returns-based tests, we find evidence of a significant state-level component in the operating performance and capital investments of *EC* firms, i.e., sales and investments of firms with economic interests in a U.S. state are correlated with sales and investments of firms that are headquartered in that state.

Overall, the results from the validation tests support the basic premise of the paper, which posits that local economic shocks may "travel through space" because the economic interests of firms are geographically dispersed. The citation-based measure of economic proximity indeed reflects economic connections between firms whose headquarters may be geographically distant.

2.5. Other Proximity Measures

Our main measure of proximity is based on the citation fractions of states in a firm annual report. For robustness, we also examine other measures of proximity based on physical distance, culture and industrial composition. Next, we describe these alternative measures.

2.5.1 Physical Proximity

The physical distance index is the distance in miles between population-weighted state centroids. The population-weighted state centroids coordinates are based on U.S. 2000 Census data and

[3] The R^2 in the "No HQ/EC" models is very large because for each state-level time-series, the "No HQ/EC" portfolio includes a very large fraction of the market. Thus, when we regress the "No HQ/EC" index on the market portfolio index, the R^2 is almost 1.

available from the U.S. Census Bureau.[4] Given the coordinates of the centroids, for each state i-state j pair, we measure distances using the great-circle or orthodromic distance formula:

$$d_{i,j} = 3963 \times \{acos(sin(lat_i) \times sin(lat_j) + cos(lat_i) \times cos(lat_j) \times cos(long_j - long_i))\}, \quad (3)$$

where $lat_{i/j}$ and $long_{i/j}$ are state i/j's population-weighted centroid coordinates. To measure physical proximity, we use the inverse of $d_{i,j}$.

2.5.2 Cultural Proximity

The cultural similarity index measures the degree of similarity between the demographic features of the population in states j and i. It is based on nine state-level demographic characteristics. The following six state-level variables are from the U.S. Census: average age, average education level, population density, fraction married, fraction minorities, and male-to-female ratio. The remaining three are religiosity, Democrat-to-Republican ratio, and Catholic-to-Protestant ratio. To identify political affiliation, we use the state-level Presidential elections data. The religiosity of a state and the proportions of Catholics and Protestants in a state are based on the religious adherence data from the "Churches and Church Membership" files available through the American Religion Data Archive (ARDA). All demographic variables are measured over the 1992 to 1998 period.

To compute the index, we first standardize the nine demographic variables so that each has zero mean and a standard deviation of one. Using the state-level standardized demographics, we calculate the cultural distance between pairs of states as follows:

$$d_{i,j} = \sqrt{\sum_{k=1}^{9} (s_{i,k} - s_{j,k})^2}, \quad (4)$$

where $(s_{i,k} - s_{j,k})$ is characteristic k's distance between state i and j. Finally, we define the cultural proximity index as:

$$p_{i,j} = \frac{1}{1 + d_{i,j}}. \quad (5)$$

2.5.3 Industrial Proximity

The industrial proximity index measures the degree of similarity between the industry composition of states i and j. The industry composition is based on the five sector classification by Ken

[4]The data are available at http://www.census.gov/geo/www/cenpop/statecenters.txt.

French expanded to eight sectors to separate "Energy" from "Manufacturing", "Mining" from "Others", and "Agriculture" from "Consumer".[5] To compute the index, we first use sales data from COMPUSTAT to obtain the fraction of aggregate state-year sales attributable to each of these eight macro-sectors. Given the state-level sector sales shares, we calculate distance between industry compositions of state pairs as follows:

$$d_{i,j} = \sqrt{\sum_{k=1}^{8} (s_{i,k} - s_{j,k})^2}, \tag{6}$$

where $(s_{i,k} - s_{j,k})$ is sector's k sales share distance between state i and j. Finally, we define industrial proximity as:

$$p_{i,j} = \frac{1}{1 + d_{i,j}}. \tag{7}$$

We compute the p weights for the fiscal years 1990 to 1998 and use the average across these years to compute the weights w used in the estimation exercise.

2.6. Spatial Similarity Matrices

We use the various proximity indices to construct similarity weights w. Specifically, for a given state i, the weight w_{ij} measures the influence of state j on state i. For example, when we consider the economic proximity indices (EP), the weight $w_{i,j}$ is defined as:

$$w_{i,j} = \frac{EP_{i,j}}{\sum_{j=1}^{N} EP_{i,j}}, \tag{8}$$

The weights for state i are scaled to sum to one, i.e., $\sum_{j=1}^{N} w_{ij} = 1$ for all i. The weight w_{ii} is set to zero such that state i is not linked to itself.

The weights w_{ij} are organized in an $N \times N$ spatial matrix W. The proximity matrices related to economic, cultural, and industry similarities are denoted by $W(EC)$, $W(CULT)$, and $W(IND)$, respectively. A small (large) weight signify a weak (strong) connection between two states. The $W(D)$ matrix measures the physical distance, where a larger weight indicates greater physical distance between two states. We transform this matrix to define the $W(1/D)$ matrix, which captures physical proximity. Here, a larger weight indicates lower physical distance or greater physical proximity between two states.

[5] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/changes_ind.html for the sector classification.

2.7. Summary Statistics: Proximity Measures

We present the descriptive and summary statistics for our proximity indices and macroeconomic variables in Tables 1 and 2. Table 1 reports the three most connected states for each HQ state based on each of the four proximity indices. When we use the economic proximity measure, the rankings reveal that California, New York and Texas are frequently the most economically relevant for other states. However, they are not always the most significant economic centers. For example, for firms headquartered in South Carolina, the most economically relevant states are Florida, North Carolina, and Georgia. And for West Virginia, the most important economic centers are Virginia, Ohio, and Kentucky.

When we compare the state rankings based on economic and physical proximity measures, we do observe some overlap. This is consistent with the intuition that economic connections can be fostered more easily among firms that are in the same geographical area. In contrast, we do not observe frequent overlap between the most important EC states and the states with highest cultural or industrial proximity. These results are reported in columns (6) to (12) of Table 1.

In Table 2, we present additional statistics related to the proximity indices. Specifically, in Panel A, we present the correlation coefficient estimates for the raw unweighted proximity indices. The correlation coefficients show that the EP index is only weakly correlated with the cultural and industrial proximity indices. Consistent with the rankings in Table 1, we find that the EP index are correlated with physical distance. But the correlation coefficient is only -0.221, which suggests that the EC links are not merely a reflection of physical proximity.

Overall, the citation fractions, which form the basis of our economic proximity index, are not simply a measure of the economic size of a state where the largest states are always the most economically relevant. Economic proximity is not strongly related to cultural or industrial similarity. Finally, although economic proximity is associated with physical proximity, the state-level economic links do not merely reflect physical proximity.

2.8. Visualizing the Economic Network

For our empirical tests, we transform the raw proximity indices into weights w. We present a snapshot of the EP weights in Figures 1 and 2. Figure 1 shows the average weight that a state takes on as the EC of firms headquartered across the other 49 states, i.e., the average of w_{ij} for EC state j over all HQ states i. As expected, California, New York, and Texas are the most important EC states. However, also Delaware, Florida, Illinois, Virginia, and Washington are important economic centers. In Figure 2, we present the largest w for each HQ state, i.e., the maximum value of w_{ij} for each HQ state i. The maximum weights range from about 10 to 70 percent. Specifically, there are five state-pairs that have an EP weight above 30 percent: Alaska (HQ) and Washington (EC), Maine (HQ) and New York (EC), Michigan (HQ) and California (EC), Vermont (HQ) and Massachusetts (EC), and West Virginia (HQ) and Virginia (EC).

Overall, there is significant heterogeneity in the economic proximity weights. To further highlight this heterogeneity, we present a visualization of the 50×50 economic proximity weights matrix in Figure 3. We group values of the state-to-state economic proximity index into the following six bins: below 2 percent, 2-5 percent, 5-10 percent, 10-20 percent, 20-50 percent, and above 50 percent. Darker (lighter) shades denote progressively larger (smaller) values of the economic proximity index. The heat map indicates that no state is truly isolated. Even geographically distant states such as AK and HI have strong economic connections with at least one U.S. state. Moreover, although CA, NY, and TX are the most frequent highly relevant states as expected, only very few states (e.g., AK, HI, ND, and WV) are least economically relevant to all states.

The network of economic connections is more evident in Figure 4, where we show the state-level connections using dominant economic links only. To identify dominant economic links, we consider economic proximity values of 5 percent and above. Solid lines identify strong economic links while dashed lines identify moderately strong links. The figure indicates that the network of state-level economic connections is not symmetric. Further, either directly or indirectly, many far away states are economically connected. Indeed, although some state-pairs do not have strong direct (i.e., first degree) connections, they have strong second degree connections through the U.S. economic hubs of CA, NY, and TX.

2.9. Summary Statistics: Macroeconomic Variables

In Table 2, Panel B, we present summary statistics for the variables used in our forecasting analysis. A brief description of these variables is available in Appendix C. The sample period for our empirical analysis is from 1999 to 2010. We choose this sample period to ensure that the measurement period of the economic proximity index (1996 to 1998) is different from the estimation period of the forecasting regressions (1999 to 2010). We separate the measurement period of the proximity index and the estimation period of the forecasting regressions to avoid spurious correlations that can arise from the "reflection" problem (Manski (1993)).

Our main variable of interest is the growth rate of the real per capita Gross State Product (GSP) of all private non-government businesses provided by the Bureau of Economic Analysis. The average GSP growth rate is about 1.1 percent and it is volatile as the mean standard deviation is about 2.5 percent. The measure is also moderately persistent. The correlation coefficient of GSP growth with its lagged values is 0.380.[6] In addition, the GSP growth rate of a state is positively correlated with the average past GSP growth of other economically relevant states. In the following sections, we use a multivariate regression framework to test whether this positive correlation is strong and robust.

3. Baseline Estimates

In this section we present our main results. First, we describe our empirical model and estimation technique followed by our baseline estimation results. We also discuss the economic significance of our findings.

3.1. Estimation Method

Our empirical model is designed to test whether the economic conditions in a particular state i can be predicted using the past economic conditions in other states that are economically relevant for state i. In particular, we estimate the following spatial dynamic panel model:

$$Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}, \qquad i = [1, ..., N],\ \ t = [1, ..., T],$$

where Y_{it} is the economic conditions of state i in year t. The model includes a time-lagged dependent variable ($Y_{i,t-1}$) to account for any persistence in Y. The vector X_{it} is a $1 \times K$ vector of control variables, the constant c_i is the state fixed effect, and the random variable η_{it} is the error term. To make the model as realistic as possible, we assume that the error term and the control variables are contemporaneously correlated. We allow for endogenous control variables because at the aggregate level it is hardly ever the case that a shock to GSP growth is uncorrelated with

[6] We examine whether the GSP growth rates are stationary using the panel unit root test of Levin, Lin and Chu (2002) and the panel stationary test of Hardi (2000). We find that the null unit root hypothesis of Levin et al. (2002) is rejected at conventional significance levels, while the null stationarity hypothesis of Hardi (2000) cannot be rejected.

other state-level aggregates that can serve as control variables.

The main independent variable is the spatially lagged dependent variable $\sum_{j=1}^{N} w_{ij} Y_{j,t-1}$, where Y is lagged GSP growth and the weights w_{ij} measures the influence of state j on state i. Because the weights for state i sum to one, the spatially lagged dependent variable is a weighted average. We use various measures of proximity to define the weights matrix W. Our main dependent variable is the growth rate of the real per capita Gross State Product (GSP) of all private non-government business.

The two main control variables are the state relative population size and agricultural GSP weight. The state relative size captures any unobserved effects related to the size of a state that are not accounted for by the state fixed effects. The agricultural GSP weight models the unique economic conditions of states that are heavily concentrated in agriculture. Following Asdrubali, Sorensen and Yosha (1996), Kalemli-Ozcan, Reshef, Sorensen and Yosha (2010), and Korniotis and Kumar (2011), we consider additional control variables like the GSP weight in manufacturing, the GSP weight in mining, and the level of state industry concentration. Because none of these variables are significant in the empirical model, we omit them from the analysis.

The estimation of the empirical model is quite challenging. Specifically, the ordinary least squares estimator is biased because of the incidental parameter problem arising from the presence of state fixed effects and the lagged dependent variable Y_{t-1}. This bias is amplified due to the presence of the spatial lagged dependent variable WY_{t-1} and the endogenous control variables. Korniotis (2010) shows that traditional instrumental variable estimators that address these three sources of bias have very poor finite sample properties. Therefore, we adopt the bias correction estimator in Korniotis (2010), which is consistent, asymptotically normal, and has good finite sample properties.[7]

3.2. Potential Endogeneity Concerns

The main objective of our empirical exercise is to test whether the spatially lagged dependent variable $\sum_{j=1}^{N} w_{ij} Y_{j,t-1}$ is significant when the weights are based on our new measure of economic proximity. One potential concern with this empirical strategy is that the average GSP growth of EC states may predict economic growth of the HQ state because of omitted common national shocks that affect all U.S. states.

[7] To conserve space, a detailed description of the estimator is provided in the appendix.

We address this concern in multiple ways. In our main analysis, we estimate predictive regressions instead of contemporaneous regressions to ensure that state-by-state correlations due to contemporaneous national shocks do not inflate the economic significance of EC states. Our baseline regression specifications also include the past GSP growth of the HQ state, which should absorb some the effects of common national shocks.

We also address the endogeneity concerns using several robustness tests. First, we re-estimate our baseline models using GSP growth rates in excess of contemporaneous U.S. GDP growth. Next, as a placebo test, we conduct a randomization experiment where we assign random EP weights to the HQ state-EC states pairs. If common national shocks drive our results, then the economic conditions of these random EC states should predict the economic conditions in the HQ state. Most importantly, to establish causality from the economic conditions in EC states to those in the HQ state, we use the monetary losses from natural disasters in EC states as an instrumental variable (IV).

3.3. Baseline Estimates Using the Economic Proximity Measure

We present the baseline results in Table 3, where we test whether the GSP growth of EC states can predict the GSP growth of HQ states. The estimation results indicate that changing economic conditions in EC states predict the economic conditions in HQ states. Specifically, in regression (1), the estimate on the spatial lagged dependent variable is positive and statistically significant (estimate = 0.294, t-statistic = 2.22). The effect of economic growth of the EC states on the HQ states is also economically significant. For example, a one percent change in the GSP growth of New York leads to a 0.023 percent increase in the average change in the GSP growth of its connected states, which translates into a 2.1 percent change relative to the average GSP growth of 1.1 percent.

In Figure 5, we present the average effect of a one percent change in the GSP growth of a state on all other HQ states.[8] We find sizeable effects for several states other than California, New York and Texas. For example, in the case of Illinois, a one percent change in its GSP growth is followed by an average change in the GSP growth of its connected state of 0.010 percent, which translates into a 1.1 percent change relative to the average GSP growth.

[8] We compute the average economic impact of an EC state on an HQ state as follows. First, we multiply the estimate of the spatial lagged dependent variable ρ with the weight w_{ij}. Then, we average the product over all j and multiply it by one percent. Thus, the average economic effect of EC state j is $\rho \sum_{j=1}^{N} w_{ij}/N$.

These average effects mask significant cross-sectional differences. For example, we find that the economic effects are much larger when we focus on the HQ state that is most affected by an EC state. For example, Maine is most affected by the economic conditions in New York, and a one percent increase in the GSP growth of New York leads to a 0.167 percent increase in the GSP growth of Maine. This increase represents a 15.20 percent increase with respect to the average GSP growth of Maine, which is 1.10 percent. Similarly, West Virginia is most strongly connected with Virginia. A one percent increase in the GSP growth of Virginia leads to a 0.211 percent increase in West Virginia's GSP growth, which is about a 15.07 percent increase relative to the average GSP growth of West Virginia (= 1.70 percent).

We also measure the long-term effects of a local economic shock.[9] The long-term effects capture the indirect effects of an EC state shock on an HQ state through its impact on other states that are also connected to the HQ state. Specifically, in Figure 5 we plot the average effect of a one percent growth in each state on all other states in the next one, two, three, four, and five years. We only consider up to five years since after five years the effect of an economic shock almost disappears.

We find that the average impact of a one percent shock in the EC state almost doubles when we compute the long-term average effect of a local economic shock. For example, in Figure 2, we observe that a one percent increase in the GSP growth in California (Washington) leads one-year ahead to an average increase in the GSP growth of the connected states of about 2 (1.6) percent relative to the average GSP growth of 1.1 percent. Eventually, as shown in Figure 5, relative to the average GSP growth, the California (Washington) shock generates a 3.8 (2.0) percent increase in the average GSP growth of connected states. Overall, our findings demonstrate that local economic shocks can have an economically meaningful impact on the economies of connected states for up to five years.

[9] We compute the long-term impact of a shock as follows. First, using recursive substitution, we compute the long-term form of the dynamic panel: $Y_t = \sum_{s=0}^{\infty} \Psi^s (c + X_{t-s}\lambda + \eta_{t-s})$. Here, Ψ is an $N \times N$ matrix defined as $\Psi = (\pi I + \rho W)$, where I is the identity matrix and W is the matrix with all the proximity weights. The matrix Ψ^s captures the s-period effect of an economic shock. Next, for each s, where $s = 1, 2, \ldots, 5$, we compute Ψ^s and set the diagonal elements of Ψ^s to zero and define Φ_s, where Φ_s captures the s-period impact of a shock excluding the impact of the shock on the state from which it originates. We report the average effect of a shock in state j that was initiated s periods back as $\sum_{j=1}^{N} \Phi_{s,ij}/N$, where $\Phi_{s,ij}$ is the ij^{th} element of Φ_s. Last, we divide the average effect with the average GSP growth of 1.1 percent.

3.4. Impact of Local Economic Shocks on the U.S. GDP

Our baseline regression estimates and economic effect calculations suggest that the GSP growth of HQ states is systematically affected by the economic conditions in EC states. In this section, we use our baseline results to estimate the effect of EC state economic shocks on the aggregate U.S. economy. Specifically, we compute the impact of a one percent increase in EC GSP growth on U.S. GDP growth. We consider both the short-term one-year effect of an EC shock as well as its long-term cascading effects on the U.S. GDP growth.[10]

To quantify the impact of EC state economic shocks on GDP growth, we first compute the change in the GSP growth of all HQ states effected by an EC state shock. Then, we aggregate the HQ GSP changes and obtain their value-weighted average, where the weights are based on the relative GSP of states (i.e., GSP of a state divided by the total GSP of all states). The value-weighted aggregation transforms the state-level effects to aggregate GDP effects. Last, we divide the aggregate effect by the average GDP growth for our sample period, which is 1.2 percent. The one-year ahead effect of a one percent growth in an EC state j on HQ state i is $\rho \times w_{ij}$. For the long-term economic effects, the impact of a one percent GSP shock in EC state j on HQ state i measured s periods ahead is $\Phi_{s,ij}$, where $\Phi_{s,ij}$ is the ij^{th} element of the matrix Φ raised to the power of s, Ψ is $(\pi I + \rho W)$, I is the identity matrix, and W is the matrix with the economic proximity weights. The estimates for π and ρ are 0.102 and 0.294, respectively, from the baseline regression (Column (1)) in Table 3.

In Figure 6, we summarize the short-term and long-term effects of a one percent increase in EC GSP growth on GDP growth one to ten years ahead. We find that the economic impact of EC state GSP shocks on GDP growth is quite large. For example, a one percent GSP shock in California and Texas leads to a 0.08 and 0.07 percent increase in the GDP growth next year, respectively. These effects are substantial as they represent a 6.71 percent and a 5.62 percent increase in U.S. GDP, relative to the average GDP growth of about 1.2 percent. Even among smaller states, the impact of GSP shock on GDP growth is large. For example, a one percent increase in the GDP growth of the state of Washington leads to a 0.04 percent increase in the U.S. GDP growth, which represents a 3.73 percent increase relative to the average GDP growth.

The impact of local economic shocks on GDP growth is persistent and lasts for about ten

[10] We thank Vasco Carvalho for suggesting this analysis.

years. However, most of the impact on GDP growth takes place in the first few years. To illustrate the average time it takes for an average EC shock to dissipate, we present the impulse response function for a one percent shock in the GSP growth (see Figure 7). The plot indicates that, on average, 55 percent of the total effect of an EC shock is experienced in the first year. About 26 percent of the total effect is realized in the second year and about 92 percent of the total effect is realized during the first three years.

Overall, the short-term and long-term effects on aggregate GDP growth implied by our baseline regression estimates are economically large and relatively persistent.

3.5. Amplification Effects of Other Proximity Measures

Economic proximity can interact with other forms of proximity, which can potentially strengthen the impact of economic linkages. Specifically, we investigate whether physical, cultural, and industrial proximity amplifies the effects of economic proximity. To conduct this analysis, separately for each HQ-state i, we divide all remaining 49 states in two groups, high and low proximity, along the other dimensions of proximity. Then, we estimate our baseline specification focusing on the economic links of states that are, in turn, most similar or dissimilar with respect to each HQ-state. For example, when we examine the amplification effects of physical distance, for each HQ-state i we set the EC weights w_{ij} to zero for nearby (distant) states j, i.e., EC-states with physical distance from i below (above) i's median state-to-state distance. We use the same approach with cultural and industrial proximity measures and create conditional economic links.

We re-estimate the baseline regressions using these conditional economic links and report the estimates in columns (2) to (7) of Table 3. The results indicate that the economic conditions in far-away and close-by EC states have similar effects on the HQ state (see columns (2) and (3)). Similarly, we find that industrial proximity does not affect this relation (see columns (6) and (7)). The coefficient estimates and t-statistics of the spatial lagged dependent variable are almost identical when we focus on EC states with similar industries as the HQ state (estimate $= 0.274$, t-statistic $= 2.11$) or on EC states with different industrial composition than the HQ state (estimate $= 0.283$, t-statistic $= 2.35$).

Examining the potential amplification effects of cultural proximity, we find that the strength of the linkages between economically connected states is affected considerably by the degree of cultural similarity between EC and HQ states. Specifically, when we focus on the connectivity with EC states that are culturally similar to the HQ state, the coefficient estimate of the spatial lagged dependent variable is 0.339 (t-statistic = 2.63). But when we only consider links with EC states with different cultural environment than the HQ state, the coefficient estimate of spatial lagged variable drops to 0.146 and becomes statistically insignificant (t-statistic = 1.33).

Perhaps unexpectedly, but in line with the evidence from Figure 4, our tests show that state-to-state economic proximity is *not* mere reflection of the state-to-state physical proximity. In fact, although the propagation of GSP shocks across economically connected states is somewhat larger when we restrict the analysis to nearby states, the effect is of a similar order of magnitude and remains statistically significant for distant states. Our evidence of the importance of cultural similarity for the transmission of local economic shocks is a novel finding. It suggests that economic relations are more easily created and fostered when the cultural backgrounds of economic agents (e.g., managers, suppliers, and customers) are similar. This finding is consistent with the evidence in Guiso, Sapienza and Zingales (2009) who show that cultural homogeneity can foster trust between populations and facilitate economic activity.

3.6. A Case Study: The Economic Impact of Natural Disasters

Our results can be used to estimate the overall economic impact of large natural disasters after taking into account the hypothetical spillover effects from the state economy to the national economy. For example, storm Sandy in 2012 had the greatest impact on the states of New Jersey and New York. Our estimation results suggest that the indirect cumulative 10-year effect of a one percent change in the per capita GSP growth of New Jersey and New York on per capita GDP growth of the U.S. would be 0.05 and 0.15 percent, respectively, due to their centrality in the network of economic connections.

If the damages from Sandy were to slow down the GSP growth of New York and New Jersy by one percent in 2012, this would translate into a predicted incremental loss of $(0.20/100)\times 13\times 10^9 =$ \$26 billion in the next ten years, or \$2.6 billion a year, due to cascading effects.[11] This spillover effect is economically meaningful and would add to the direct damages of the storm in the affected areas, which are estimated to be about \$60 billion. The indirect losses would be large in this case because New Jersey and New York are states with frequently strong economic connections with other U.S. states.

[11]We multiply the 0.20 percent change in GDP growth with the level GDP in 2011, which was about 13 trillion dollars.

In contrast, similar computations for hurricane Katrina produce considerably smaller estimates because Katrina affected mainly Louisiana and Mississippi, which are not major economic centers. Specifically, if the damages from Katrina had slowed down the GSP growth of Louisiana and Mississippi by one percent in 2005, the predicted indirect loss in GDP 10-years ahead would have been about 8.9 billion dollars.[12]

4. Insights Into Shock Propagation Mechanisms

Our baseline results indicate that economic links created by the geographical distribution of publicly-traded firms transmit economic conditions across the U.S. economy. The propagation of shocks is especially strong among states that are culturally similar. In this section, we present results from additional tests, which allow us to identify the mechanisms that facilitate the propagation of economic shocks. The results from these tests are summarized in Table 4.

4.1. Impact on Employment and Investment Growth

In our baseline empirical analysis, we focus on the growth of gross state product because it is the most comprehensive measure of economic activity. However, GSP, being a measure of output, has to be related to inputs. This implies a natural auxiliary hypothesis. Improving economic conditions in EC states should improve employment and increase capital investments in the HQ state. Higher levels of employment and increased investments in the HQ state would eventually result in an increase in the GSP of the HQ state. We test this auxiliary hypothesis using data on state-level employment and investments.

We present the evidence from these input-based tests in Table 4. In regression (1), the dependent variable is the state-level employment growth and the estimation time period is 1999 to 2010. In regression (2), the dependent variable is state-level investment growth and the estimation time period is from 1999 to 2007.[13]

We find that the GSP growth in economically linked states affects the employment growth in the HQ state. Specifically, the coefficient estimate of the spatial lagged dependent variable in

[12]This predicted loss is based on an estimated cumulative indirect (spillover) 10-year effect on GDP growth of -0.037 and -0.034 percent resulting from a one percent decrease in GSP growth of Louisiana and Mississippi, respectively. Given that U.S. GDP in 2005 was 12.5 trillion dollars, in economic terms the spillover effects of Katrina is about 8.9 billion dollars ($= (0.037 + 0.034)/100 \times 12.5$ trillion).

[13]This estimation period ends in 2007 because the investment data from Yamarik (2012) are only available till 2007. We have to rely on the investment data produced in Yamarik (2012) because the Bureau of Economic Analysis does not produce a state-level investments series.

regression (1) is 0.639 (t-statistic = 2.33). When we examine the growth in capital investments across states, we find that an improvement in economic conditions in EC states induces higher investments in the HQ state. The coefficient estimate of the spatial lagged dependent variable is positive and significant (estimate = 0.197, t-statistic = 2.61).

These results provide additional support for our key conjecture and indicate that local economic shocks in EC states affect the production input, labor and capital, markets of economically connected HQ states.

4.2. Dominant Economic Centers

We find that on average the economic links facilitate the propagation of economic shocks across the U.S. economy. It is plausible that the source of all major economic shocks are only a handful of important economic centers. In this section, we investigate whether our results reflect the impact of the following five most economically relevant states: California, New York, and Texas, followed by Delaware and Washington. In regression (3), the weights w_{ij} are based on economic proximity with all states, excluding California, New York, and Texas. These are the three states with the largest average number of citations. In regression (4), we further exclude economic links with Delaware and Washington.[14]

We find that the predictive ability of our state-level economic network is not driven by economic connections with a handful of dominant states. In regression (3) where we exclude the three largest states, the remaining states strongly predict GSP growth in HQ states. The coefficient estimate of the spatial lagged dependent variable is 0.351 and the t-statistic is 2.44. We obtain similar estimates in regression (4) where we exclude the top 5 most cited states. These results indicate that our main results reflect the effects of economic connections among all states rather than economic connections with only a few dominant states.

4.3. Proportion of Publicly-Traded Firms in the Local Economy

Our conjecture about the geographical propagation of economic shocks relies on the implicit assumption that the decisions of corporate managers that are affected by the economic environment in EC states have meaningful economic effects on the HQ state economy. This logic implies that

[14]Figure 1 shows that Delaware is the fourth most important economic center, which may be partly due to the fact that many companies are incorporated in this state. Thus, economic events related corporate litigation tend to cluster in this state and may affect Delaware's citation shares.

impact of shocks in EC states on the economy of HQ states should be stronger in HQ states where publicly-traded firms represent a larger fraction of the local economy.

We test this prediction in regressions (5) and (6) of Table 4. We measure the weight of publicly-traded firms in the HQ state economy as the ratio of state-level corporate profits and GSP. We use this ratio to redefine the economic proximity weights. In regression (5), if an HQ state i has a ratio below the bottom 10^{th} percentile, then all w_{ij} weights are set to zero. That is, the economic activity in state i can affect the economic conditions in other states, but the economic activity in state i is not affected by economic shocks in other states. Similarly, in regression (6), we set the weights to zero if an HQ state i has a ratio below the bottom 20^{th} percentile.

Consistent with our conjecture, when we exclude HQ states where publicly-traded firms carry little weight, we find that the impact of the EC network on HQ state GSP growth increases slightly. In particular, when we consider all HQ states, the coefficient estimate of the spatial lagged dependent variable is 0.294 (see Table 4, regression (1)) and this estimate rises to 0.371 and 0.343 in regressions (5) and (6), respectively. This evidence supports the notion that the activities of publicly-traded firms facilitate the propagation of economic shocks from EC states to the HQ state.

4.4. Propagation of the Sales Growth of Publicly-Traded Firms

In this section, we provide *direct* evidence that the economic activity of publicly-traded firms in HQ states is affected by economic activity of firms in economically linked states. If firms in EC states conduct business with firms in HQ states, the performance of firms in EC states should have a direct impact on the performance of HQ firms. To test this conjecture, instead of predicting GSP growth, we predict the sales growth of public firms in HQ states using the past sales growth of firms in EC states. We use sales growth in our analysis because it is the closest firm-level measure corresponding to GSP growth.

We present the sales growth regression in column (7) of Table 4. We find that sales growth of public firms in EC states predicts sales growth of public firms in HQ states (estimate = 0.413, t-statistic = 2.74). This result confirms our intuition that the propagation of economic conditions through economic linkages are related to firm performance as captured by sales growth. We also examine whether the GSP growth of EC states predicts the sales growth of firms in the HQ state. We report the estimates of this regression in column (8) of Table 4. We find that economic conditions in EC states, predict sales growth of HQ firms. Specifically, the coefficient estimate of average EC GSP growth is 2.223, which is statistically significant (t-statistic = 3.46). This evidence shows directly that economic links reflect the economic environment in states that are economically important to HQ firms and consequently affect their performance.

Collectively, the results in this section strengthen our baseline results. We show directly that economic conditions transmitted through firm-level economic linkages affects employment and investment growth. In addition, we find that transmission of economic shocks through state-level economic network is directly related to firm performance since shocks to publicly-traded firms in economically linked states as captured by sales growth affect the performance of HQ firms. We also demonstrate that our evidence does not solely reflect the effects of economically dominant states like California, New York, and Texas. However, as expected, our results strengthen when we ignore economic links to states where publicly-traded firms are a small part of the state economy.

5. Robustness Checks

Our empirical results so far show the geographical distribution of publicly-traded firms generates a state-level network connections through which local economic shocks propagate across the U.S. states. In this section, we discuss the results of a series of robustness tests, which are summarized in Table 5.

5.1. Economic or Physical Proximity?

Physical (geographical) proximity can facilitate the creation of economic links. In the next robustness test, we demonstrate that the effects of our network of EC linkages are incremental over the effects of physical proximity. For this test, we directly use the physical distance between the U.S. states. Specifically, in Table 5, regression (1), we under-weight economic links of near-by states by interacting (i.e., multiplying) the economic proximity weights with weights obtained using physical distance. We find that the spatial lagged dependent variable remains statistically significant even when we under-weight nearby states and over-weight far-away states. Thus, our results are unlikely to reflect the effects of physical proximity.

5.2. An Alternative Measure of Economic Proximity

In most of our analysis, to reduce endogeneity concerns, we use economic proximity weights measured over the 1996-1998 period. This three-year period is prior to the main estimation period, 1999-2010. In the next test (See Table (5), column (2)), we compute the proximity weights using data for the full sample period, 1996-2008. We find a similar estimate for the spatial lagged dependent variable (estimate = 0.278, t-statistic = 2.10).

In regression (3) of Table 5, we use the alternative economic proximity weights defined in Section 2.1. These weights are based on a proximity index that weighs equally the citation fractions of all firms. The estimation results with the alternative measure of economic proximity are qualitatively similar to the baseline results. Thus, our evidence of economic shock transmission across the U.S. states does not depend upon the specific methodological choices made in the construction of the state-level economic links.

5.3. Accounting for Common National Shocks

One potential concern with our results is that the significance of the spatial lagged GSP growth is induced by a missing national shock that affects the GSP growth of all states. In our main analysis, we account for national shocks by including the past GSP growth of the HQ state in the regression specification, which would capture the effects of common national shocks.

For additional robustness, in regression (4) of Table 5, we directly account for the potential impact of common national shocks directly by removing the effects of U.S. GDP shocks from the state-level measures of economic growth. Specifically, we follow the Gabaix (2011) method and replace the spatial predictor that is based on raw GSP growth (i.e., $\sum_j w_{ij} gGSP_{j,t-1}$) with a spatial predictor that is based on relative GSP growth. The relative growth measure is defined as $gGSP$ minus $gGDP$, where $gGDP$ is the U.S. real per capita GDP growth. The new predictor is:

$$\sum_{j=1}^{N} w_{ij} \left(gGSP_{j,t-1} - gGDP_{t-1} \right), \tag{9}$$

where the weights w_{ij} are the economic proximity weights. The relative GSP measure does not capture the effects of national shocks.

We find that the relative GSP growth of EC states strongly predicts the GSP growth of HQ states. The coefficient estimate of the spatial lagged GSP growth variable is 0.225 with a t-

statistic of 2.25. Therefore, it is very unlikely that common national shocks somehow mechanically generate state-level growth predictability.

5.4. A Placebo Test: Random Economic Links

In our last robustness check, we present evidence from a placebo test. To conduct this test, we randomize the economic links and assign to each HQ state random EC links drawn from the $[0, 1]$ uniform distribution. If our economic links capture a true economic connection between EC and HQ states, we should find no evidence of predictability when we use these random links.

To test this conjecture, we generate 1,000 random link matrices and re-estimate the GSP predictability regression. Consistent with our expectations, we find that the economic conditions of randomly selected states do not forecast the economic conditions of the HQ state (see Table 5, column (5)). Specifically, we find that in only 0.70% of replications the economic conditions of the random states have significant predictive power. This finding suggests that the predictive power of the average GSP growth of non-random EC states is not driven by omitted common economic shocks. Rather, the effects we document reflect the connectivity induced by the distribution of publicly-traded firms as captured by the state-level network of economic connections.

Taken together, the evidence from our robustness tests shows that the predictive power of our state-level network of economic links is robust and unrelated to the specific methodological choices. Our results are not driven by physical proximity or missing common national economic shocks. The evidence from our placebo test confirms that the state-level network reflects *actual* economic links resulting from the geographical distribution of the activities of publicly-traded firms.

6. Natural Disasters and GSP Predictability

Our evidence so far shows that state-level economic growth affects the growth of other states that are economically connected. Notwithstanding the results of our robustness tests, the potential impact of omitted common national shocks on our inferences may remain a concern. Therefore, we re-examine our baseline results using an instrumental variable estimation method.

Our key innovation is to instrument the past average growth of economically relevant states with the scaled monetary losses from natural disasters in those states. The scaled monetary losses are the total losses in the current year scaled by the state GSP in the previous year. We use state

GSP as a deflator to capture the economic magnitudes of natural disasters relative to the size of the state economy. The aggregate monetary loss from natural disasters is an appropriate instrument because it captures a local effect and it is not correlated with national economic shocks. Thus, while a local natural disaster clearly has a direct impact on the economy of the affected state, it can only affect other states through the state-level network economic connections.

6.1. Natural Disasters and Economic Growth

The results from these tests are reported in Table 6. We first examine whether natural disaster losses have an impact on the economic growth of the affected state (see Panel A). In specifications (1) and (2) of Panel A, we find that scaled state-level losses positively affect state-level economic growth. This positive relation is not mechanically due to the fact that both scaled losses and GSP growth are higher when past GSP is low. In specifications (3) and (4), we scale the disaster losses with current GSP and find that a rise in disaster losses is still positively correlated with economic growth.[15]

The finding that natural disasters spur economic growth is consistent with the Schumpeterian creative destruction process in which the rebuilding caused by natural disasters leads to re-investment and upgrading of a state's productive infrastructure (Caballero and Hammour (1994)). Previous studies such as Skidmore and Toya (2008) find similar results in a large sample of natural disasters across various countries. Cuaresma, Hlouskova and Obersteiner (2008) show that the positive relation between growth and natural disasters is especially strong in developed countries. Further, Belasen and Polachek (2008) find that hurricanes in Florida positively affect local wages. Overall, our results along with the evidence from these related studies indicate that the aggregate monetary losses from natural disasters provide a valid instrument for local economic growth.

6.2. Instrumental Variable Regression Estimates

In this section, we report instrumental variable (IV) regression estimates for our baseline results. These results are reported in Table 6, Panel B. Our IV estimator is an extension of the bias correction estimator of Korniotis (2010). The bias correction estimator accounts for the possibility that natural disasters are local and, therefore, they can affect many states that are clustered geographically. This implies that even if natural disasters are unrelated to national shocks,

[15]In our main analysis, we prefer scaling with past GSP because the current GSP includes the impact of the natural disasters.

their effects might still be correlated at the regional level. Our IV estimator takes such regional correlations into account and ensures that they do not inflate the estimates of the average GSP growth of economically relevant states. A detailed description of the estimator is in the appendix.

The IV estimation results in Panel B indicate that economic growth in a HQ state is related to the past economic growth in its EC states network. Specifically, when we use the main economic proximity measure, the results in column (1) indicate that the impact of the past average growth of EC states on the HQ state growth is high (estimate = 0.309, t-statistic = 2.45). We continue to obtain significant results in regression (2) when we exclude neighboring states from the proximity measure, under-weight the remaining nearby EC states, and over-weight far-away EC states (estimate = 0.229, t-statistics = 2.16). Further, in regression (3), we find that the propagation of shocks from the EC states network to the HQ state remains significant, even when we restrict our attention to state pairs that are far-away (i.e., above median physical distance).

Next, we examine whether the IV estimator properly accounts for the possibility that nearby states have correlated economic conditions because they experience similar regional shocks. In particular, we estimate a regression in which we consider the effects of only the near-by states (i.e., below median physical distance). These states are expected to have the most correlated regional shocks. The evidence in column (4) indicates that the economic conditions in near-by states are not strong predictors of economic conditions in HQ state (estimate = 0.241, t-statistic = 1.56). This evidence indicates that our IV estimator appropriately under-weights the significance of states that experience the same disaster events.

For robustness, in Panel C of Table 6, we report IV regression estimates with the assumption that the disaster shocks are completely exogenous and uncorrelated across all states, including the neighboring states. The results from these tests are very similar to the evidence reported in Panel B and indicates that correlated regional shocks are not driving the IV estimation results.

7. Summary and Conclusion

The United States is one political entity but its economy may be partially segmented, where each U.S. state has a distinct economy that is connected to the economies of other states. This view of a partially segmented U.S. economy is consistent with the fact that key economic indicators such as gross state product, unemployment rates, and house prices vary substantially across states.

In this paper, we adopt this view of a segmented U.S. economy and develop a state-level network of economic connections that stem from the geographical distribution of economic activities of publicly-traded firms. We use this network to examine whether local state-level shocks unrelated to national economic conditions propagate to the economies of other U.S. states.

We find that local economic shocks propagate through the state-level network of economic connections, whereby the growth of a state depends significantly on the past growth of other states to which it is linked. The evidence of predictability is stronger when two states are culturally similar but remains unaffected by geographical or industrial proximity. Our findings do not merely reflect the impact of omitted common national shocks. Using monetary losses from state-level natural disasters as an instrument, we show that state-level economic shocks propagate through the economic network generated by public companies.

These results contribute to the macroeconomics literature on economic networks, which traces the origins of aggregate national shocks to micro-level shocks (e.g., Gabaix (2011), Acemoglu et al. (2012)). We empirically identify an economic network among the U.S. states and show that local micro-level economic shocks propagate through this network. In future work, it would be useful to examine the impact of an economic network of smaller, privately-held companies. Individually these economic entities may be small but jointly they may also transmit and amplify the effects of local economic shocks.

Establishing that there are strong connections between U.S. states and that these connections affect the propagation of economic shocks has important policy implications. First, any federal transfers to a state can have positive economic implications to the states that are connected to it. Therefore, the net cost of state-targeted programs is lower when taking into account the positive spillover effects on the connected states. Second, our results underscore the importance of publicly traded firms for the U.S. economy. We show that they are the connective tissue that bonds the U.S. economy and their performance in one region can have far reaching effects in our regions. Therefore, policies to revitalize the U.S. economy may be most effective when targeted toward larger business with geographically dispersed economic interests.

Our work has also implications for asset pricing. Specifically, our work is related to the literature on how the dynamics of income shocks affect the evolution of asset pricing factors and stochastic discount factors from consumption pricing models as in Constantinides and Duffie (1996). For example, our findings suggest that the income shocks in a state are not only affected by the local economy but they are also affected by the economic shocks in connected states.

These state-by-state interrelations can create comovement in risk aversion across regions and consequently, comovement in asset prices across regions.

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TABLE 1
State Rankings Based on Proximity Estimates

The table reports the three states that are the most strongly connected to each state based on four measures of proximity: economic, physical (i.e., inverse of distance), cultural, and industrial. For each state, we report the name of the three states with the largest proximity index values. The proximity indices are described in Section 2.

	Economic Proximity			*Physical Proximity*			*Cultural Proximity*			*Industrial Proximity*		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AK	WA	NY	DE	WA	OR	MT	NV	AZ	CO	KS	ID	WA
AL	FL	TN	GA	MS	GA	TN	SC	TN	NC	NY	NV	CT
AR	DE	TX	FL	MS	MO	OK	KY	TN	MO	MI	ID	RI
AZ	TX	CA	NM	NM	UT	NV	MI	NC	WA	GA	MN	NC
CA	TX	NY	DE	NV	AZ	UT	AZ	IL	GA	MA	PA	CO
CO	CA	NY	TX	WY	NM	UT	WA	VA	AZ	KS	CA	MA
CT	NY	WA	PA	RI	MA	NY	NJ	MA	NY	NV	HI	LA
DE	TX	PA	MD	MD	NJ	NY	MI	OH	IL	ND	OR	NM
FL	NY	CA	VA	GA	SC	AL	PA	OH	DE	MN	NH	GA
GA	FL	NY	VA	SC	AL	TN	SC	NC	TX	MN	NH	FL
HI	CA	WA	NV	CA	OR	NV	CA	AZ	NM	NV	CT	VT
IA	NY	CA	IL	WI	IL	MO	WI	SD	NE	NC	VT	CT
ID	CA	TX	OR	MT	UT	OR	WY	KS	NE	MI	AR	RI
IL	NY	CA	FL	IN	MO	IA	MI	DE	NC	MN	PA	GA
IN	OH	FL	NY	IL	KY	OH	KY	OH	TN	TN	MD	UT
KS	MO	NE	NY	NE	OK	MO	NE	SD	MT	CO	MA	CA
KY	FL	OH	CA	IN	TN	OH	IN	TN	AR	MN	FL	GA
LA	TX	AR	MS	MS	AR	AL	MS	SC	AL	WI	OR	CT
MA	NY	RI	CT	RI	NH	CT	RI	CT	NJ	WA	KS	NY
MD	NY	CA	VA	DE	PA	NJ	DE	NY	IL	UT	ME	LA
ME	NY	CT	MA	NH	VT	MA	VT	OR	NH	MD	SC	OR
MI	CA	DE	NY	OH	IN	WI	OH	DE	NC	AR	RI	ID
MN	NY	CA	WI	WI	IA	SD	WI	IA	KS	FL	GA	IL

TABLE 1
State Rankings based on Proximity (Continued)

	Economic Proximity			*Physical Proximity*			*Cultural Proximity*			*Industrial Proximity*		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MO	KS	IL	NY	IL	AR	KS	TN	KY	AR	GA	IL	OH
MS	TN	LA	FL	AL	LA	AR	LA	SC	AL	IA	MO	NC
MT	ID	UT	WY	ID	WY	ND	WY	KS	WI	AZ	WI	OR
NC	FL	CA	VA	VA	SC	WV	TN	SC	AL	VT	MN	FL
ND	MT	MN	CO	SD	MN	MT	SD	NE	KS	DE	WI	OR
NE	TX	CA	UT	KS	SD	IA	KS	SD	OK	NV	WY	NC
NH	NY	NJ	MA	MA	VT	RI	VT	ME	MT	GA	FL	MN
NJ	NY	CA	DE	NY	DE	CT	CT	MA	RI	TN	IN	MA
NM	CA	NY	FL	CO	AZ	OK	IL	LA	TX	DE	OR	ND
NV	CA	MS	AZ	CA	UT	ID	AZ	MI	AK	HI	CT	NE
NY	DE	NJ	TX	NJ	CT	DE	MD	DE	IL	AL	CT	NC
OH	NY	IN	FL	WV	IN	KY	MI	TN	IN	IL	WI	MN
OK	TX	KS	AR	KS	AR	TX	SD	NE	KS	TX	WV	LA
OR	CA	WA	UT	WA	ID	NV	WA	ME	MT	SC	WI	ND
PA	DE	NY	IN	MD	DE	NJ	OH	MO	FL	IL	GA	MN
RI	MI	DE	TX	MA	CT	NH	MA	NJ	CT	MI	AR	FL
SC	FL	NC	GA	GA	NC	VA	AL	NC	GA	OR	WI	SD
SD	MT	NE	IA	NE	ND	MN	NE	ND	KS	OR	SC	ND
TN	FL	CA	TX	KY	AL	GA	MO	NC	KY	IN	NJ	UT
TX	CA	NY	LA	OK	LA	AR	OK	GA	NM	OK	VA	CA
UT	CA	NV	AZ	WY	NV	ID	TX	ID	NE	MD	MN	SD
VA	NY	CA	WA	NC	WV	MD	NC	IL	WA	GA	NH	FL
VT	MA	ME	NH	NH	MA	ME	NH	ME	OR	NC	IA	GA
WA	CA	NY	OR	OR	ID	MT	OR	CO	VA	GA	FL	MN
WI	IL	MN	AZ	MN	IA	MI	IA	SD	MO	OR	LA	SC
WV	VA	OH	KY	VA	OH	MD	KY	ME	AR	LA	ND	WI
WY	DE	CO	NY	CO	UT	MT	MT	ID	KS	NV	NE	HI

TABLE 2
Descriptive Statistics

The table reports univariate statistics (i.e., mean and standard deviation) and correlation coefficients for a set of variables. The variables (1) to (4) are the four proximity indices: economic proximity (EP), physical distance in thousands of miles (DIST), cultural proximity (CULT), and industrial (IND) proximity. The variables (5) to (11) are the main variables we use in our estimation. This set includes the growth rate of real per capital gross state product of all private non-government firms ($\mathrm{gGSP_t}$), its lagged value ($\mathrm{gGSP_{t-1}}$), its spatial lag ($\mathrm{W_{EP} \times gGSP_{t-1}}$), the relative state size based on population, the agricultural GSP weight, and the state employment and investment growth, and sales growth. Appendix C provides a brief description of all variables.

Panel A: Proximity Indices

Variable	Mean	Std Dev	(1)	(2)	(3)
(1) EP	0.010	0.019			
(2) DIST	1.233	0.916	−0.221		
(3) CULT	0.222	0.071	0.189	−0.442	
(4) IND	0.250	0.083	0.007	−0.076	0.076

Panel B: GSP Growth and Other Variables

Variable	Mean	Std Dev	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(5) $\mathrm{gGSP_t}$	0.011	0.025							
(6) $\mathrm{gGSP_{t-1}}$	0.012	0.022	0.380						
(7) $\mathrm{W_{EC} \times gGSP_{t-1}}$	0.013	0.021	0.215	0.372					
(8) Rel State Size	0.011	0.025	0.210	0.076	0.149				
(9) GSP Weight: Agri	0.012	0.023	0.256	0.038	0.080	0.350			
(10) $\mathrm{gEmp_t}$	0.013	0.020	0.077	−0.044	0.114	0.219	0.405		
(11) $\mathrm{gInv_t}$	0.000	0.027	0.182	−0.157	0.041	−0.040	0.048	0.125	
(12) $\mathrm{gSALES_t}$	0.081	0.242	0.012	0.009	−0.011	0.032	−0.039	0.000	0.136

TABLE 3
Predicting State GSP Growth Using Economic Proximity Measures

The table reports estimation results for the following model: $Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}$. In these regressions, Y is real per capita GSP growth of all private non-government firms (gGSP) and X includes relative state size and agricultural GSP weight. The model is estimated using the bias correction approach of Korniotis (2010). The t-statistics reported below the estimates are based on Driscoll and Kraay (1998) standard errors, which account for cross-sectional and serial autocorrelation in errors. The time period is from 1999 to 2010. In regression (1), the proximity weights w are based on economic proximity. In columns (2) and (3), we focus on economic links of a state with other states that are geographically nearby and far-away, respectively, i.e., for state i the weights w_{ij} are set to zero for all states with distance below and above the median distance with state i, respectively. In columns (4) and (5), we focus on economic links of a state with other states that are culturally similar and different, respectively, i.e., for state i the weights w_{ij} are set to zero for all states with cultural proximity below and above the median proximity with state i, respectively. In columns (6) and (7), we focus on economic links with states that concentrate in similar and different industries, i.e., for state i the weight w_{ij} is set to zero for all states with industrial proximity below and above the median proximity with state i, respectively. All variables and proximity matrices are defined in Appendix C and Section 2, respectively.

	Weights Matrix (W) =						
		High D	Low D	High Cult:	Low Cult:	High Ind:	Low Ind:
	W_{EC}	W_{EC}	W_{EC}	W_{EC}	W_{EC}	W_{EC}	W_{EC}
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$gGSP_{t-1}$	0.102	0.114	0.114	0.081	0.183	0.110	0.114
	(0.96)	(1.41)	(1.06)	(0.80)	(1.58)	(1.05)	(1.06)
$W \times gGSP_{t-1}$	0.294	0.210	0.288	0.339	0.146	0.274	0.283
	(2.22)	(2.08)	(2.17)	(2.63)	(1.33)	(2.11)	(2.35)
Rel State Size	−4.254	−4.236	−4.134	−4.310	−3.990	−4.234	−4.270
	(−3.88)	(−3.67)	(−3.81)	(−3.64)	(−3.66)	(−3.95)	(−3.72)
GSP Weight: Agri	−1.256	−1.146	−1.318	−1.312	−1.192	−1.277	−1.221
	(−1.78)	(−1.64)	(−1.81)	(−1.84)	(−1.64)	(−1.83)	(−1.70)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.147	0.133	0.151	0.159	0.128	0.149	0.144
N(Obs)	600	600	600	600	600	600	600

TABLE 4

Predicting State GSP Growth: Additional Evidence

The table reports estimation results for the following model: $Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}$. In regression (1), Y is the state-level employment growth and the time period is from 1999 to 2010. In regression (2), Y is state-level investment growth and the time period is from 1999 to 2007 because the investment data from Yamarik (2012) are only available till 2007. In regressions (3) to (6), Y is real per capita GSP growth of all private non-government firms (gGSP) and the time period is 1999 to 2010. In all regressions, X includes relative state size and agricultural GSP weight. The model is estimated with the bias correction approach of Korniotis (2010). The t-statistics reported below the estimates are based on Driscoll and Kraay (1998) standard errors, which account for cross-sectional and serial autocorrelation in errors. In regressions (1) and (2), the proximity weights w_{ij} are based on our main economic proximity index. In regression (3), the weights w_{ij} are based on economic proximity with all states except California, New York, and Texas. In regression (4), the weights w_{ij} are based on economic proximity with all states excluding California, New York, Texas, Delaware, and Washington. In regressions (5) and (6), we account for the relative size of publicly traded firms in a state using the ratio of the corporate state-level profits to GSP as a measure of size. The state-level profit-to-GSP ratio is averaged over the 1995 to 1998 period and we use this ratio to adjust the economic proximity weights. In particular, in regressions (5) and (6), if a state i has a ratio below the bottom 10^{th} and bottom 20^{th} percentile, respectively, then all weights w_{ij} are set to zero. In this case, the economic activity in state i can affect other states, but the economic activity in state i is not affected by other states. In regression (7), Y is state-level sales growth of publicly traded firms in a state and the proximity weights w_{ij} are based on economic proximity. In regression (8), Y is state-level sales growth of publicly traded firms in a state and main predictor is the average past GSP growth of EC states. All variables and proximity matrices are defined in Appendix C and Section 2, respectively.

	Empl. Growth	Invest. Growth	Excl. CA NY, TX	Excl. CA, NY TX, DE, WA	Profit-to-GSP		$\text{Y=}gSales_t$	$\text{Y=}gSales_t$
					$> 10^{th}$	$> 20^{th}$	$\text{X=W}\times gSales_{t-1}$	$\text{X=W}\times gGSP_{t-1}$
Ind/ Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{gGSP}_{\text{t}-1}$	0.073	−0.361	0.080	0.100	0.056	0.085	−0.244	−0.254
	(0.28)	(−4.99)	(0.77)	(0.96)	(0.50)	(0.78)	(−2.57)	(−2.89)
$\text{W}\times\text{gGSP}_{\text{t}-1}$	0.639	0.197	0.351	0.306	0.371	0.343	0.413	2.223
	(2.33)	(2.61)	(2.44)	(2.08)	(2.31)	(2.12)	(2.74)	(3.46)
Rel State Size	−3.604	−3.446	−4.342	−4.278	−4.277	−4.160	−14.610	−14.050
	(−1.65)	(−0.47)	(−4.06)	(−3.93)	(−3.83)	(−3.66)	(−3.55)	(−2.88)
GSP Agri W	0.123	−0.131	−1.277	−1.210	−1.230	−1.170	−4.87	−3.11
	(0.27)	(−0.02)	(−1.81)	(−1.72)	(−1.75)	(−1.65)	(−1.92)	(−1.03)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.408	0.123	0.157	0.145	0.150	0.140	0.065	0.074
N(Obs)	600	550	600	600	600	600	600	600

TABLE 5
Predicting State GSP Growth: Robustness Tests

The table reports estimation results for the following model: $Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}$. In regressions (1) to (4), and (6), Y is real per capita GSP growth of all private non-government firms (gGSP), while in regression (5) it is the growth in per capita value added from state and local governments. In all regressions, X includes relative state size and agricultural GSP weight. The model is estimated with the bias correction approach of Korniotis (2010). The t-statistics reported below the estimates are based on Driscoll and Kraay (1998) standard errors, which account for cross-sectional and serial autocorrelation in errors. The time period is from 1999 to 2010. In regression (1), we interact (i.e., multiply) the economic proximity weights with physical distance between the EC and HQ states. In regressions (4) and (5), the proximity weights w_{ij} are based on our main economic proximity index computed using data over the 1996 to 1998 period and in regression (2) they are computed using data from 1996 to 2008. In the remaining regressions, the economic proximity index is based on data from 1996 to 1998. In regression (3), we use alternative economic proximity weights. In regression (4), we account for the impact of national shocks by removing the effects of U.S. GDP shocks from the spatial lagged variable. In particular, we replace $\sum_{j=1}^{N} w_{ij} gGSP_{j,t-1}$ with $\sum_{j=1}^{N} w_{ij} \left(gGSP_{j,t-1} - gGDP_{t-1}\right)$, where $gGDP$ is the U.S. real per capita GDP growth and w_{ij} are the economic proximity weights. In regression (5), the dependent variable is real per capita GSP growth of the government sector (i.e., value added to a state's GSP from the government sector). In regression (6), we randomize the proximity weights and assign random EC links to HQ states. Specifically, we draw random weights from a uniform distribution 1,000 times, estimate the predictability model, and collect the estimates from all those replications. We report the average estimates from the replications and in the brackets below the estimates, we report the percentage of times the estimate is negative and significant (number on the left hand side) and the percentage of times the estimate is positive and significant (number on the right hand side). We also report the average adjusted R^2 from all the replications. All variables and proximity matrices are defined in Appendix C and Section 2, respectively.

	Dependent Var. = Private Sector $gGSP_t$				
	$W_{EC} \times W_D$	W_{EC}	W_{EC}	Excl. GDP	Random
	96-98	96-08	Altern.	Shocks	Weights
Ind. Var.	(1)	(2)	(3)	(4)	(5)
$gGSP_{t-1}$	0.081	0.109	0.094	0.121	0.121
	(0.80)	(1.01)	(0.90)	(1.13)	[0.00, 0.00]
$W \times gGSP_{t-1}$	0.339	0.278	0.325	0.225	0.314
	(2.63)	(2.10)	(2.22)	(2.25)	[0.00, 0.70]
Rel State Size	−4.310	−4.266	−4.310	−4.242	−4.163
	(−3.64)	(−3.84)	(−4.00)	(−3.72)	[100.00, 0.00]
GSP Agri W	−1.3126	−1.260	−1.250	−1.297	−1.188
	(−1.84)	(−1.76)	(−1.80)	(−1.76)	[0.00, 0.00]
State FE	Yes	Yes	Yes	Yes	Yes
(Avg) Adj R^2	0.159	0.146	0.150	0.149	0.138
N(Obs)	600	600	600	600	600

TABLE 6
Predicting GSP Growth: Instrumental Variables Regression Estimates

Panel A reports the estimation results from panel regressions with state fixed effects where the dependent variables is GSP growth. The independent variables are scaled total monetary losses due to natural disasters, the relative size of a state, and the state's agricultural GSP weight. In specifications 1 and 2, we divide the natural disaster losses with past GSP, and in regressions 3 and 4, we divide with current GSP. The regressions are estimated with ordinary least squares. The t-statistics reported below the estimates are based on Driscoll and Kraay (1998) standard errors, which account for cross-sectional and serial autocorrelation in errors. The time period is from 1999 to 2010. In Panel B, we report estimation results for the following model: $Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}$. Y is real per capita GSP growth of all private non-government firms (gGSP) and X includes relative state size and agricultural GSP weight. The model is estimated with an instrumental variables (IV) version of the bias correction estimator of Korniotis (2010). The IV estimator instruments the spatial lagged dependent variable, $(\sum_{j=1}^{N} w_{ij} Y_{j,t-1})$, with $(\sum_{j=1}^{N} w_{ij} D_{j,t-1})$, where D is the scaled natural disaster losses (i.e., total losses in year $t-1$ divided by GSP in year $t-2$). The IV corrected estimator takes the following from: $\left(\widetilde{X}'Z\right)^{-1}(Z'Y - B)$, where $\widetilde{X}$ includes the independent variables, Z replaces the independent variables with their instruments, Y is the GSP growth rate, and B is the bias correction term. In Panel C, we report IV estimates setting the bias B for the spatial lagged dependent variable to zero. Again, the t-statistics reported below the estimates are based on Driscoll and Kraay (1998) standard errors, which account for cross-sectional and serial autocorrelation in errors. The time period in all regressions is 1999 to 2010. In regression (1), the proximity weights w are based on economic proximity. In regression (2), we interact the economic proximity weights with physical distance between the states and set the weights of all neighboring states to zero. In regressions (3) and (4), we focus on economic links with far-away and nearby states, respectively, i.e., for state i the weights w_{ij} are set to zero for j states with physical distance below and above the median distance with state i, respectively. All variables and proximity matrices are defined in Appendix C and Section 2, respectively.

Panel A: Natural Disasters and Local GSP Growth

Independent Variables	(1)	(2)	(3)	(4)
Loss-GSP Ratio_{t-1}	0.035	0.031		
	(3.34)	(3.33)		
Loss-GSP Ratio_{t}			0.033	0.028
			(2.88)	(2.73)
Rel State Size		−2.555		−2.555
		(−2.43)		(−2.43)
GSP Weight: Agri		0.366		0.367
		(1.68)		(1.68)
State FE	Yes	Yes	Yes	Yes
Adj R^2	0.001	0.010	0.001	0.010
N(Obs)	600	600	600	600

TABLE 6
Impact of Natural Disasters (Continued)

Panel B: IV Regression Estimates With Local Correlations

	Weights Matrix (W) =			
		Neigh = 0	High D:	Low D:
	W_{EC}	$W_{EC} \times W_D$	W_{EC}	W_{EC}
Independent Variables	(1)	(2)	(3)	(4)
$gGSP_{t-1}$	0.086	0.128	0.133	0.170
	(0.89)	(1.33)	(1.40)	(1.19)
$W \times gGSP_{t-1}$	0.309	0.229	0.219	0.241
	(2.45)	(2.16)	(2.25)	(1.56)
Rel State Size	−4.158	−4.293	−4.140	−3.902
	(−3.78)	(−3.75)	(−3.55)	(−3.41)
GSP Weight: Agri	−1.141	−1.067	−1.036	−1.229
	(−1.66)	(−1.56)	(−1.53)	(−1.64)
State FE	Yes	Yes	Yes	Yes
Adj R^2	0.135	0.122	0.122	0.153
N(Obs)	600	600	600	600

Panel C: IV Regression Estimates Without Local Correlations

$gGSP_{t-1}$	0.089	0.131	0.134	0.174
	(0.91)	(1.33)	(1.40)	(1.20)
$W \times gGSP_{t-1}$	0.302	0.223	0.216	0.234
	(2.36)	(2.06)	(2.20)	(1.49)
Rel State Size	−4.148	−4.278	−4.134	−3.894
	(−3.76)	(−3.73)	(−3.55)	(−3.39)
GSP Weight: Agri	−1.140	−1.067	−1.037	−1.227
	(−1.66)	(−1.56)	(−1.53)	(−1.64)
State FE	Yes	Yes	Yes	Yes
Adj R^2	0.134	0.121	0.121	0.152
N(Obs)	600	600	600	600

FIGURE 1

Average Economic Impact of Each State on Other U.S. States

This figure shows the average effect of each state i on all other states based on the weights of economic proximity. Specifically, we report the value of $100 \times \sum_{i=1}^{N} w_{ij}/N$ for each state.

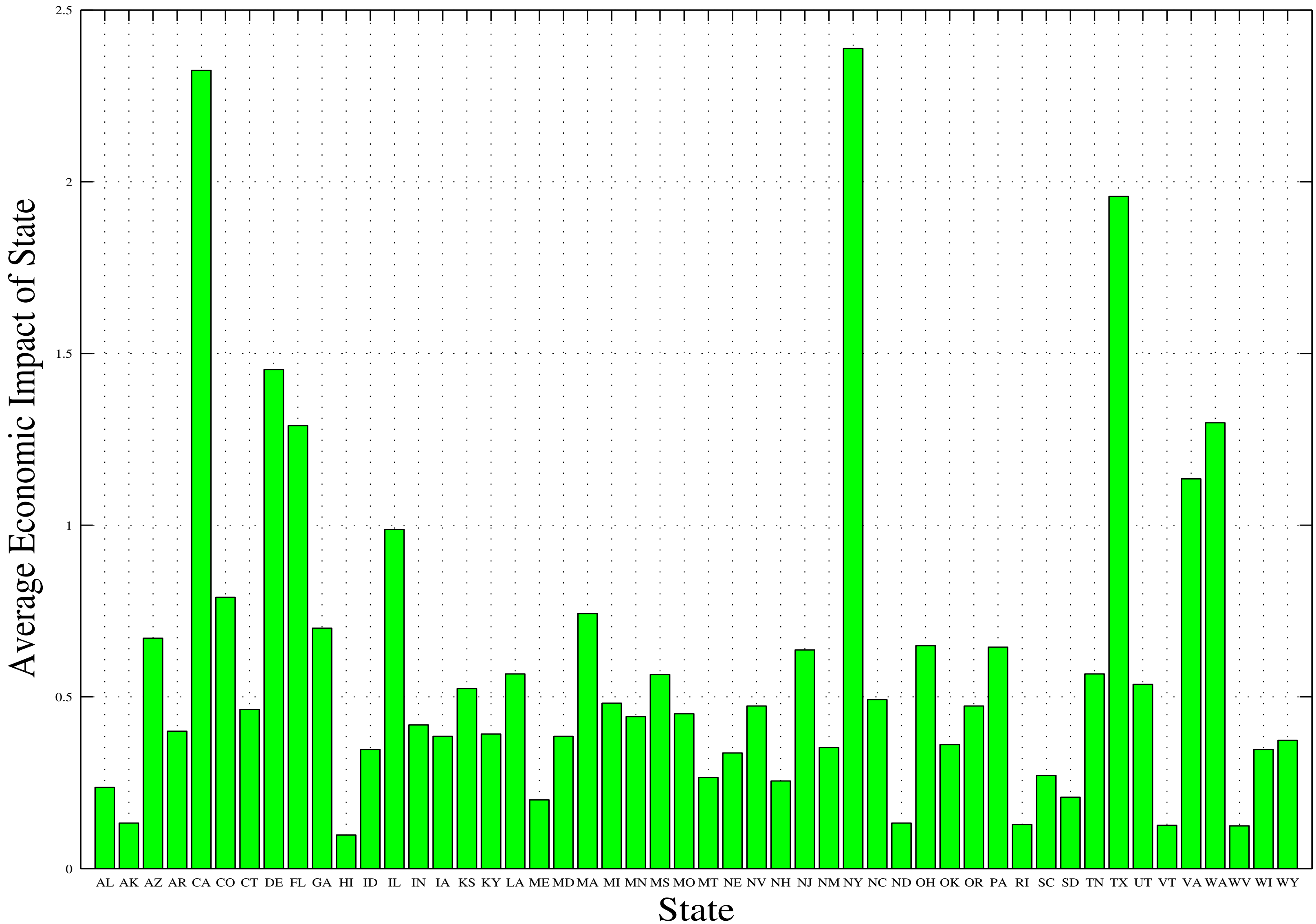


FIGURE 2

Largest Economic Impact on Each State

This figure shows the maximum effect on each state i based on the weights of economic proximity. Specifically, we report the value of $\max_{j=1}^{N} 100 \times w_{ij}$ for each state.

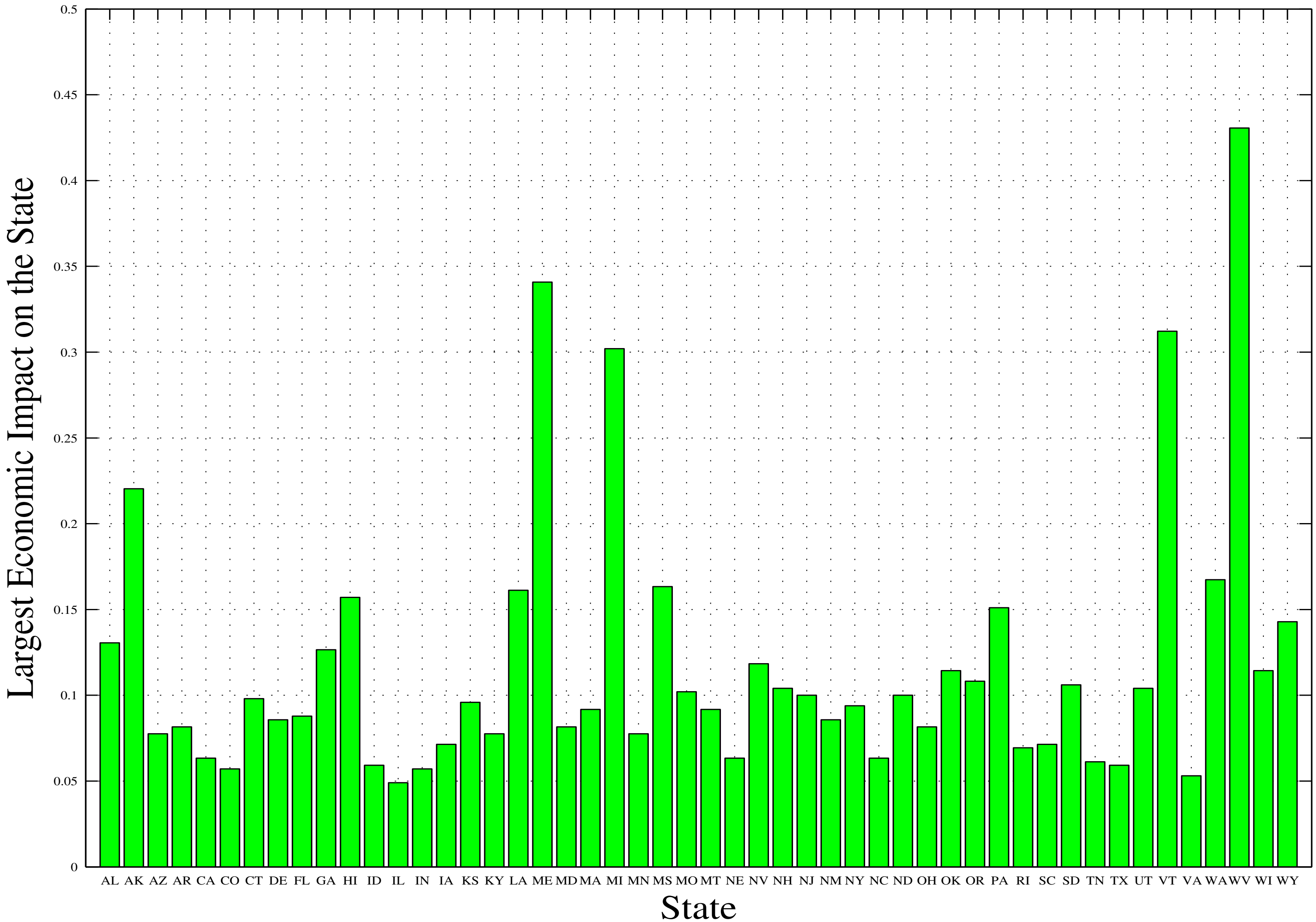


FIGURE 3
State-to-State Value-Weighted Economic Proximity Index

This figure shows the state-to-state value-weighted economic proximity index values grouped in the following six bins: below 2%, 2-5%, 5-10%, 10-20%, 20-50%, and above 50%. Darker (lighter) shades denote progressively larger (smaller) values of the economic proximity weight for a state-pair.

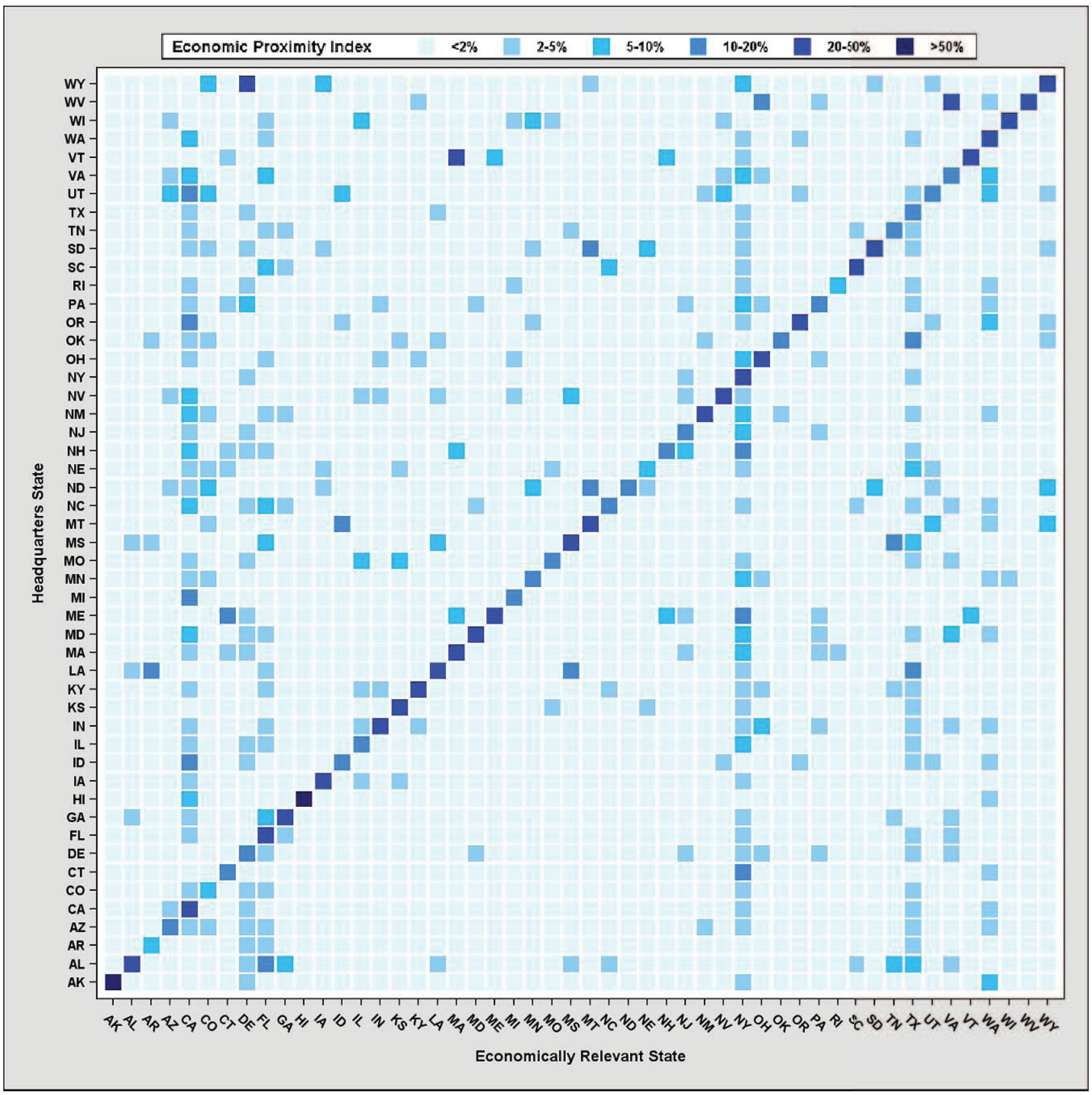


FIGURE 4

Economic Network of U.S. States

The figure shows the state-level economic network where the connections are based on value-weighted economic proximity indices. To identify dominant economic links, we only consider economic proximity estimates of 5% and above. Strong economic links are indicated using solid lines while moderately strong links are identified using dashed lines. Specifically, dashed (continuous) intra-state arrows denote economic proximity weights less than or equal to (greater than) 20%. Dashed (continuous) inter-state arrows denote economic proximity weights less than or equal to (greater than) 10%. A circle arrow around a state label denotes an intra-state connection. An arrow from ER-state i to HQ-state j denotes inter-state connection.

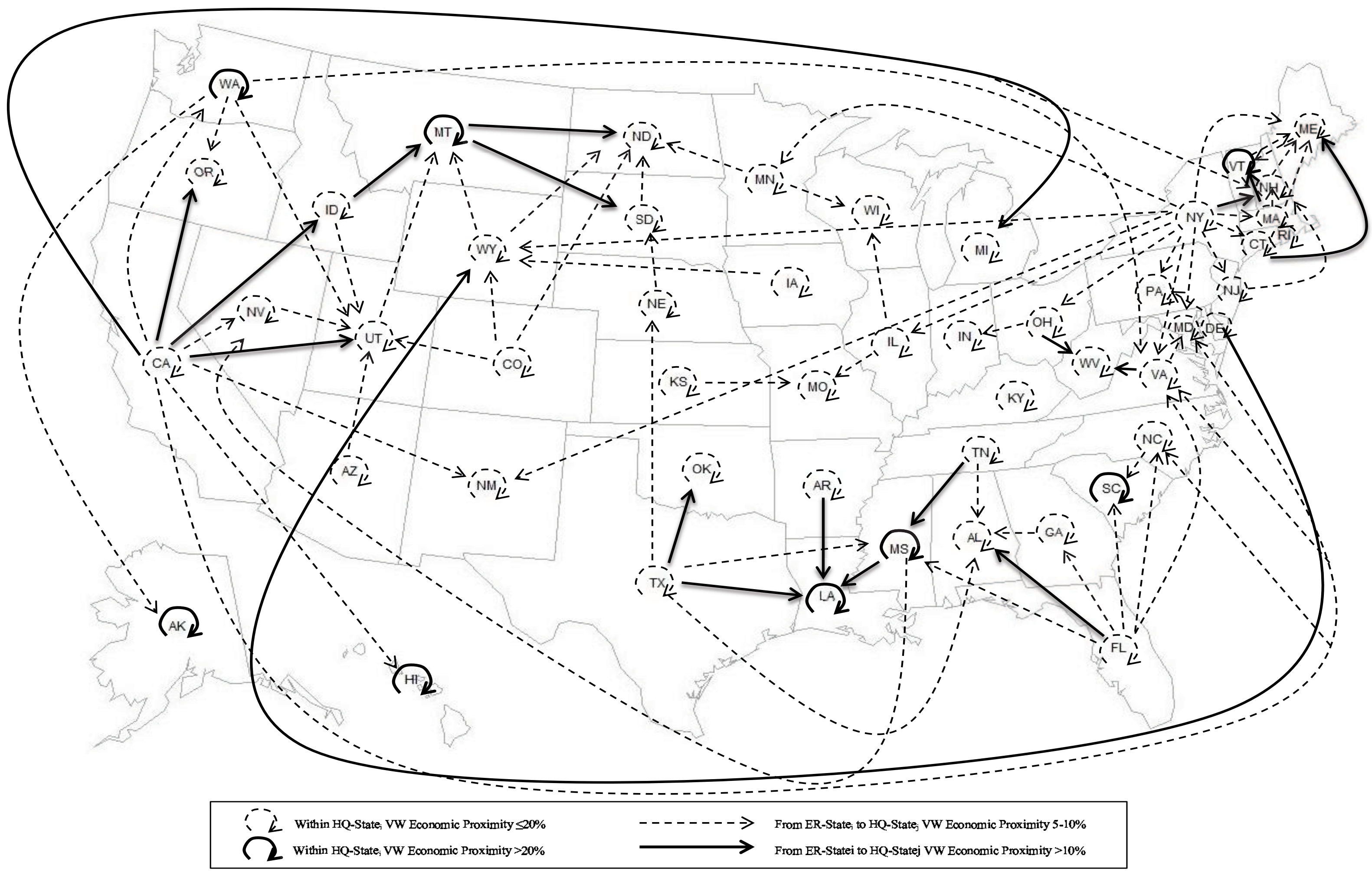


FIGURE 5

Average Long-Term Economic Impact of a Local Economic Shock

This figure shows the average effect of a one percent increase in the GSP growth of an EC state on the GSP growth of HQ states s-years ahead, where $s = 1, 2, \ldots, 5$. The one-year ahead effect from a one percent growth in the EC state j is $\rho \sum_{j=1}^{N} w_{ij}/N$. For the long-term economic effects, the average effect of a one-percent GSP shock in EC state j s periods ahead is $\sum_{j=1}^{N} \Phi_{s,ij}/N$, $\Phi_{s,ij}$ is the ij^{th} element of the matrix Φ raised to the power of s, Ψ is $(\pi I + \rho W)$, I is the identity matrix, and W is the matrix with the economic proximity weights.

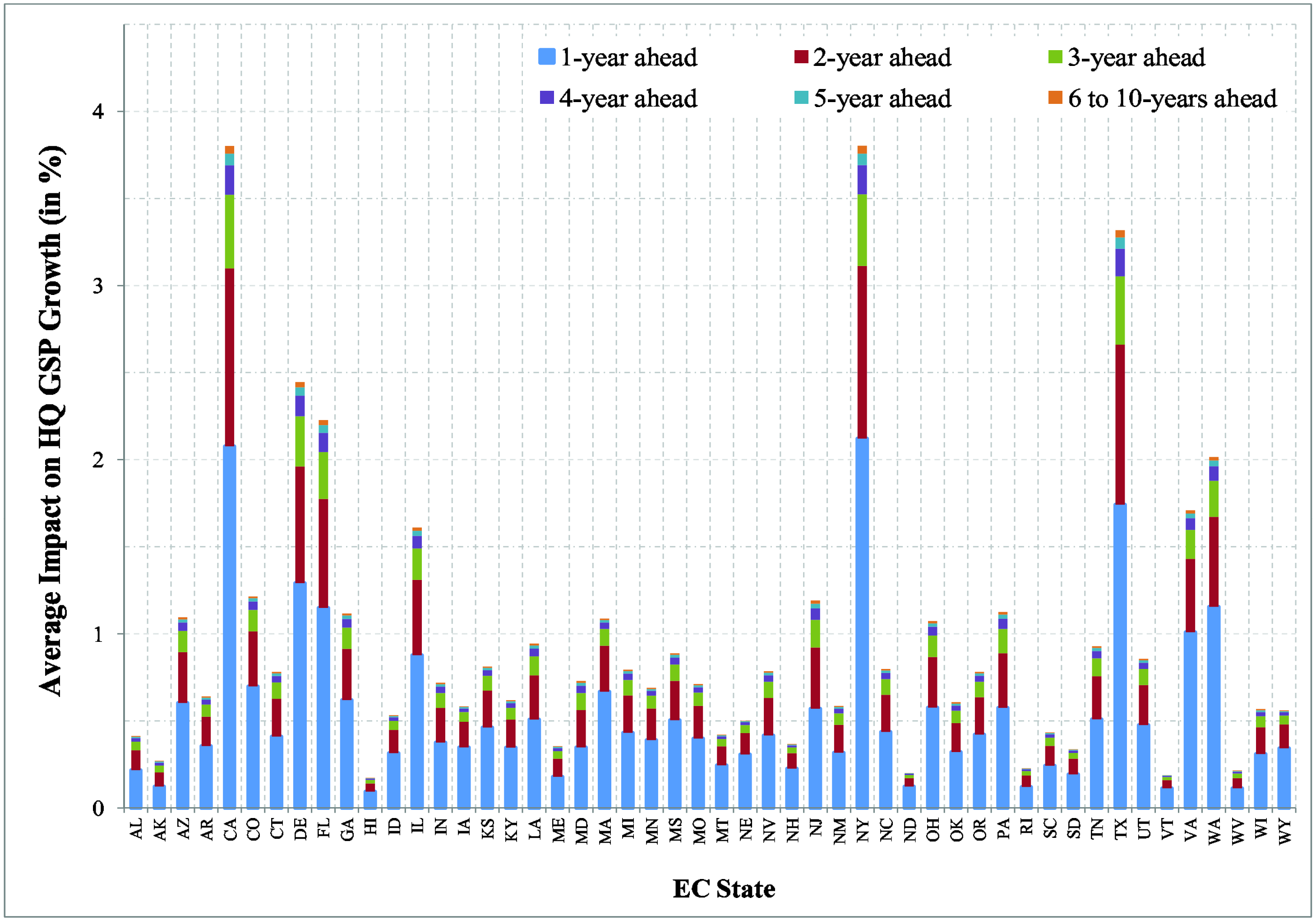


FIGURE 6

Long-Term Economic Impact of a Local Shock on the U.S. GDP

This figure shows the effect of a one percent increase in the GSP growth of an EC state on the U.S. GDP growth s-years ahead, where $s = 1, 2, \ldots, 10$. To compute the impact on GDP growth, first, we compute the change in the GSP growth of all HQ states effected by the EC state shocks. Second, we aggregate the HQ GSP changes using a value-weighted average where the weights are based on the relative GSP (i.e., GSP of a state to the total GSP across all states). And third, we divide the aggregate effect with the average GDP growth. In the first step, the one-year ahead effect on HQ state i from a one percent growth in the EC state j is $\rho \times w_{ij}$. For the long-term economic effects, the effect of a one percent GSP shock in EC state j on HQ state i measured s periods ahead is $\Phi_{s,ij}$. Here, $\Phi_{s,ij}$ is the ij^{th} element of the matrix Φ raised to the power of s, Ψ is $(\pi I + \rho W)$, I is the identity matrix, and W is the matrix with the economic proximity weights. The π and ρ estimates are 0.102 and 0.294, respectively, and are taken from the baseline regression (Column (1)) in Table 3.

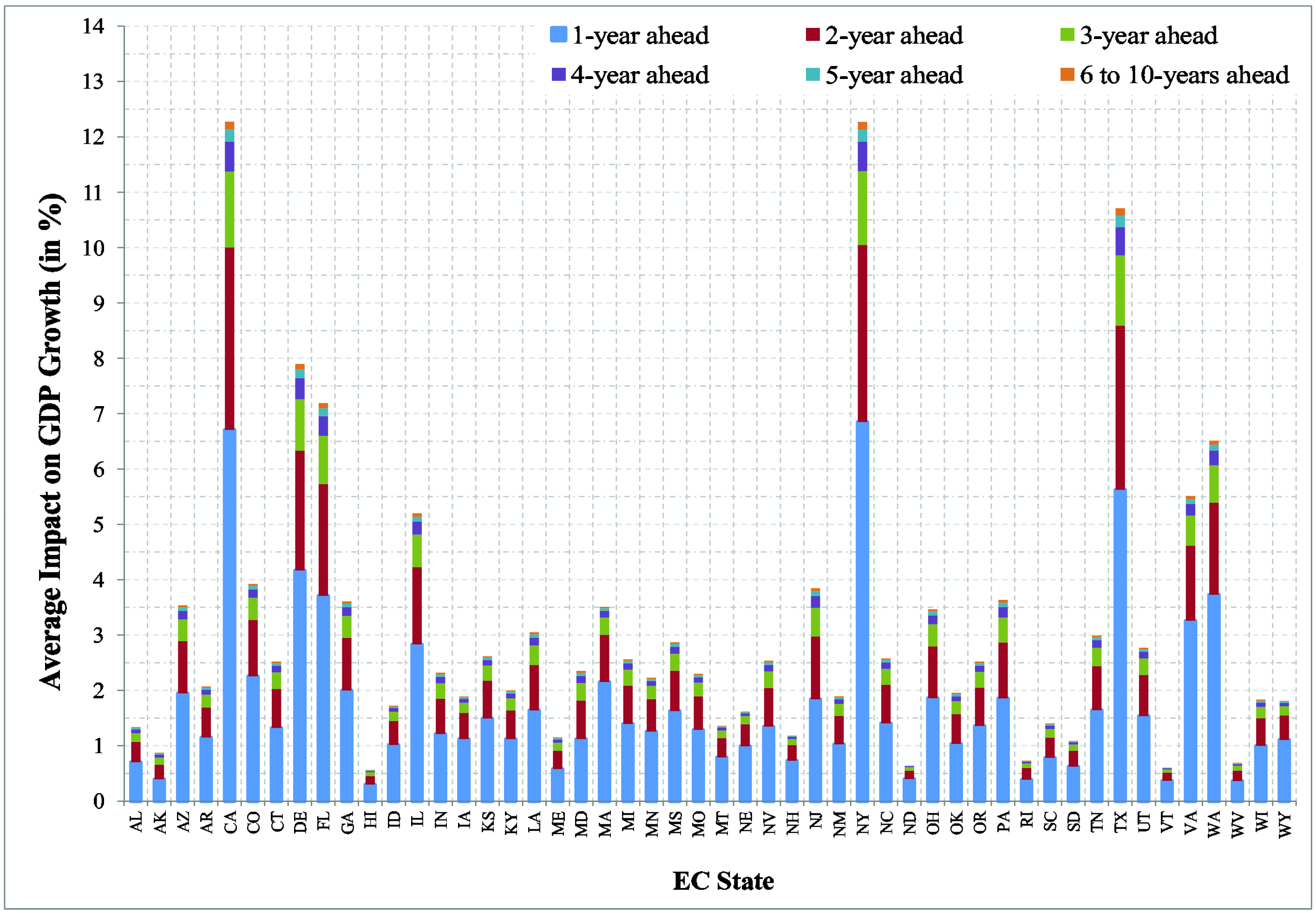
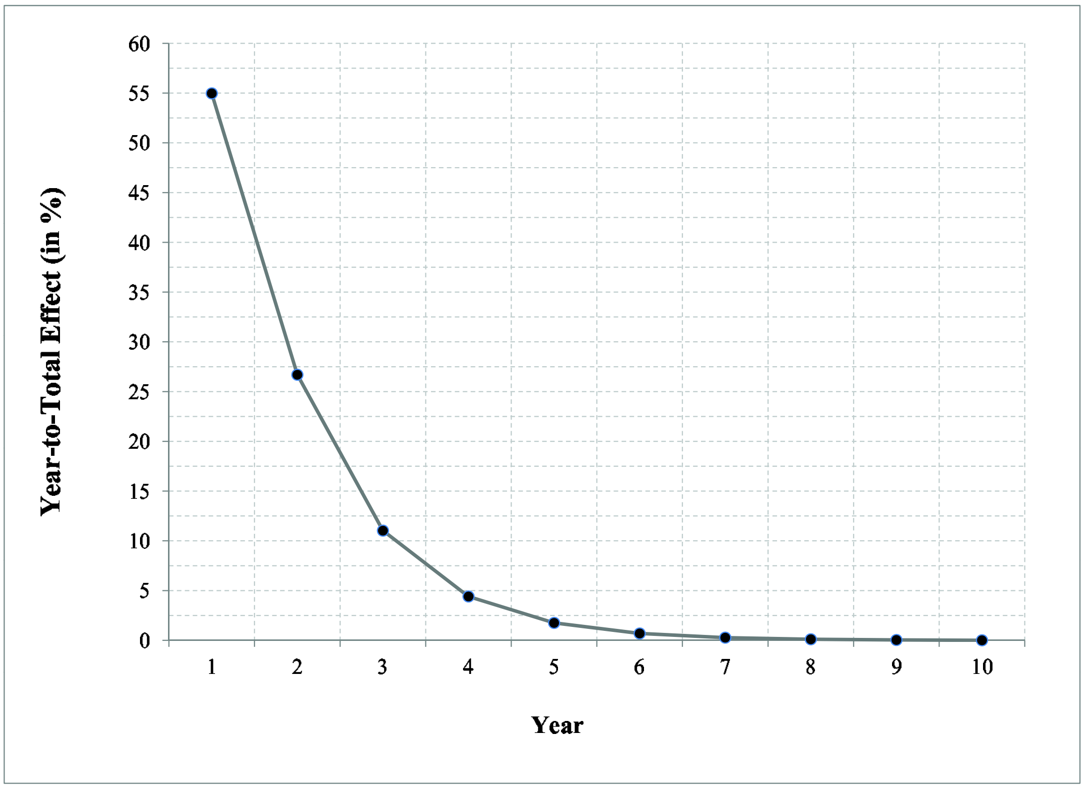


FIGURE 7

Impulse Response: Economic Impact of a Local Economic Shock on the U.S. GDP

This figure shows the impulse response of a one percent increase in EC GSP growth s-years ahead, where $s = 1, 2, \ldots, 10$. For each s, we report the percentage of the total effect on GDP growth that took place in year s, averaged across all states. The average impact of an EC shock on GDP growth is computed as in Figure 6.



Appendices

Appendix A: Information Content of 10-K Fillings

In this appendix, we briefly describe the content of a typical 10-K fillings and especially items 1, 2, 6, and 7. This discussion closely follows Bernile et al. (2010).

The federal securities laws require companies issuing publicly traded securities to disclose information on an ongoing basis. Notably, Section 13 or 15(d) of the Securities Exchange Act of 1934 ("the Act") requires companies with more than 10 million dollars in assets and whose securities are held by more than 500 owners to file an annual report (Form 10-K) providing a comprehensive overview of the company's business and financial condition.

A 10-K must be filed within 90 days after the end of the fiscal year covered by the report. This form contains information such as company history, organizational structure, executive compensation, equity, subsidiaries, and audited financial statements, among other information. Regulation S-K outlines the reporting requirements for various SEC filings used by public companies, including Form 10-K. Although this standardized form contains four parts and 15 schedules, for the purpose of our analysis, we focus on Items 1, 2, 6, and 7.

In particular, Section 229.101 of Regulation S-K requires that Item 1 in Form 10-K summarizes the general development of the business of the filing company, its subsidiaries and any predecessor(s) during the prior five years. Specifically, this item provides the following information: (i) the year in which the registrant was organized and its form of organization; (ii) the nature and results of any bankruptcy, receivership or similar proceedings with respect to the registered company or any of its significant subsidiaries; (iii) the nature and results of any other material reclassification, merger or consolidation of the company or any of its significant subsidiaries; (iv) the acquisition or disposition of any material amount of assets otherwise than in the ordinary course of business; and (v) any material changes in the mode of conducting the business.

The business description is expected to include all material information about the company's (i) principal products or services and their markets; (i) distribution methods; (iii) competitive position in the industry and methods of competition; (iv) sources and availability of raw materials, and principal suppliers; (v) dependence on major customers; (vi) patents, trademarks, licenses, franchises, concessions, royalty agreements, or labor contracts; (vii) need for any government approval of principal products or services; (viii) effect of existing or probable regulations; (ix) research and development activities; and (x) number of employees.

Item 2 of Form 10-K, pursuant to Section 229.102, lists the location and general character of the principal plants, mines, and other materially important physical properties of the company and its subsidiaries. In principle, this item should include any information that will inform investors as to the suitability, adequacy, productive capacity and extent of utilization of the facilities by the company. However, a detailed description of the physical characteristics of individual properties is not required.

Section 229.301 requires for Item 6 of Form 10-K to supply selected financial data that highlight significant trends in the company's financial condition and operating performance. The following items are expected to be included: (i) net sales or operating revenues; (ii) income (loss) from continuing operations; (iii) income (loss) from continuing operations per common share; (iv) total assets; (v) long-term obligations and redeemable preferred stock (including long-term debt, capital leases, and redeemable preferred stock); and (vi) cash dividends declared per common share.

Finally, pursuant to section 229.303, Item 7 of the annual report includes the management's discussion and analysis ($MD\&A$) of the company's financial condition and results of operations. The purpose of $MD\&A$ is to provide readers with information that may help their understanding of the financial data included in the annual report. This section is intended to meet three broad objectives: (i) provide a narrative explanation of a company's financial statements that enables investors to see the company through the eyes of management; (ii) enhance the overall financial disclosure and provide the context within which financial information should be analyzed; and (iii) provide information about the quality and potential variability a company's earnings and cash flow, so that investors may assess the extent to which past performance is indicative of future performance.

Specifically, the $MD\&A$ is expected to identify current trends, deficiencies, and commitments, and highlight any expected changes pertaining to the company's liquidity and capital resources. Moreover, it should identify unusual events or significant economic changes that materially affected the reported operating results, and describe any known trends or uncertainties that have had or are expected to have a favorable or unfavorable impact on the company's operations. Finally, the discussion should provide explicit information regarding off-balance sheet arrangements that have or are likely to have an effect on the company's financial performance.

Appendix B: Excerpts From 10-K Fillings

In this appendix, we present examples of excerpts from actual 10-K fillings, which we extracted from the SEC's EDGAR system. In particular, we report passages that appear in Items 1, 2, 6, or 7 of a firm's annual report. These examples are from Bernile et al. (2010).

Example 1: RELM WIRELESS CORPORATION

(CIK 0000002186, Form 10-K filed on 2008-03-05)

Item 1 - Business. Our principal executive offices are located at 7100 Technology Drive, West Melbourne, Florida 32904 ... In June 2007, one of our dealers was awarded a contract to be the exclusive supplier of BK Radio-brand P-25 digital portable radios and accessories to the West Virginia Division of Forestry ... In May 2007, the California Department of Forestry (CDF) extended its contract with our authorized RELM BK Radio dealer ... In May 2007, we received a certificate of award for a contract to be a supplier of two-way radio communications equipment to the state government of North CarolinaAs of December 31, 2007, we had 101 full-time employees, most of whom are located at our West Melbourne, Florida facility.

Item 2 - Properties. We lease approximately 54,000 square feet of industrial space at 7100 Technology Drive in West Melbourne, Florida ... We also lease 8,100 square feet of office space in Lawrence, Kansas, to accommodate a segment of our engineering team.

Item 7 - MD&A. We lease approximately 54,000 square feet of industrial space at 7100 Technology Drive in West Melbourne, Florida ... We also lease 8,100 square feet of office space in Lawrence, Kansas, to accommodate a segment of our engineering team.

Example 2: LEHMAN T H & CO INC

(CIK 0000721647, Form 10-KSB filed on 2001-06-29)

Item 1 - Business. Effective October 27, 1989, the Company acquired all of the outstanding stock of Self Powered Lighting, Inc. a New York corporation with offices in Elmsford, New York ("SPL") from an entity affiliated with two of the Company's directors ... Presently, the company has one client, which operates a specialty clinic in the Los Angeles, California area ... effective February 1, 1993, the Company purchased Healthcare Professional Billing Corp. (HPB), in Broomfield, Colorado.

Item 2 - Properties. The Company presently has an administrative sharing arrangement which, among other things, provides use of other office facilities in Houston, Texas. MedFin Management Corporation leases office space in Burbank, California under an operating lease.

Appendix C: Variable Definitions

GSP Growth (gGSP). Growth rate of real per-capital gross state product of all private non-government firms. *Source:* Bureau of Economic Analysis.

Relative State Size. Ratio of state to U.S. population. *Source:* Bureau of Economic Analysis.

Agricultural GSP Weight. Ratio of agricultural sector GSP to GSP from all private firms. *Source:* Bureau of Economic Analysis.

State Employment Growth. Annual growth rate of state employment. *Source:* Bureau of Labor Statistics.

Profit to GSP Ratio. Aggregate state-level operating profit to state GSP. The aggregate state-level operating profit is sales minus cost of goods sold aggregated across all firm headquartered in the state.

Investment Growth Rate. The growth rate of state investments where state investments are the log difference in the state private business capital series constructed by Yamarik (2012) for the 1990-2007 period. Yamarik (2012) uses the procedure in Garofalo and Yamarik (2002) to distribute the national U.S. capital stock estimates to the states using the one-digit NAICS industry income data.

Sales Growth. It is the annual sales-weighted average sales growth of public firms headquartered in a given state. It is defined as follows for each state i and year t:

$$gSALES_{i,t} = \sum_{j=1}^{N_{i,t-1}} \frac{SALES_{j,i,t-1}}{GSP_{i,t-1}} \times \frac{SALES_{j,i,t} - SALES_{j,i,t-1}}{SALES_{j,i,t-1}},$$

where $SALES_{j,i,t}$ is the sales of firm j headquartered in state i during year t, $GSP_{i,t-1}$ is the gross state product of state i for year $t-1$, $N_{i,t-1}$ is the total number of public firms headquartered in state i during year $t-1$. The firm-level state data and the firm location are from COMPUSTAT.

Losses from Natural Disasters. To compute the monetary losses from disasters, we first compute the total county-level losses as the sum of property damages and crop losses across various natural disaster events. Then, we aggregate the county-level losses to the state level. Using the

SHELDUS database, we consider various natural hazard events like avalanches, droughts, earthquakes, flooding, fog, hail, heat, hurricanes, tropical storms, landslides, lightning, severe storms and thunder storms, tornados, wildfire, wind, and severe winter weather. *Source:* Spatial hazard events and losses database for the United States (SHELDUS) maintained by the Hazards and Vulnerability Research Institute.

Appendix D: Estimation Methodology

In this section, we present the technical details related to the estimation methodology. The discussion follows the analysis in Korniotis (2010).

Empirical Model

The empirical model we estimate is the following:

$$Y_{it} = \pi Y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} Y_{j,t-1} + X_{it}\lambda + c_i + \eta_{it}, \qquad i = [1, ..., N], \;\; t = [1, ..., T],$$

where Y_{it} is the dependent variable for state i at year t. The random variable η_{it} is the error term, which can be correlated with the control variables X. We allow for such correlations because at the aggregate level most control variables are endogenous. The constant c_i is the state fixed effect. The vector X_{it} is a $1 \times K$ vector of control variables. The model includes a time-lagged dependent variable, $Y_{i,t-1}$ and the spatially lagged dependent variable $\sum_{j=1}^{N} w_{ij} Y_{j,t-1}$. The weights w_{ij} measure the influence of state j on state i and are organized in an $N \times N$ matrix W. It is important for the weight matrix W to be uncorrelated with the error term η.

The ordinary least squares estimator of the model is biased because of the incidental parameter problem arising from the presence of state fixed effects and the lagged dependent variable Y_t. This bias is amplified due to the presence of the spatial lagged dependent variable WY_{t-1} and the endogenous control variables. To account for these three sources of bias, Korniotis (2010) proposes a bias correction estimator that is consistent, asymptotically normal, and has very good finite sample properties.

Bias-Corrected Estimator

The bias-corrected estimator is the least-squares dummy-variable estimator augmented with a bias term:

$$\hat{\phi}_c = \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{Z}^d_{i,t-1})'(\tilde{X}^d_{i,t-1})\right]^{-1} \times \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{Z}^d_{i,t-1})'Y^d_{it} - \frac{B}{\sqrt{NT}}\right],$$

where the superscript d denotes data that have been rescaled (de-meaned) with state-specific averages. The matrix $\tilde{X}_{i,t-1}$ is a $1 \times (K+2)$ data matrix equal to $(Y_{i,t-1},\ W_iY_{t-1}, X_{it})$, X_{it} is a $1 \times K$ vector of control variables, W_i is the i^{th} row of the spatial matrix W, and Y_{t-1} is a vector with the Y observations for the N states at time $t-1$. The matrix $\tilde{Z}_{i,t-1}$ is identical to $\tilde{X}_{i,t-1}$ with only one difference: the X_{it} is replaced with its lagged value $X_{i,t-1}$. We replace (instrument) the control variables with their lagged values because the control variables are endogenous and the covariance between X_{it} and η_{it} is not zero.

The vector B includes the bias correction terms that arise from the presence of the fixed effects, the lagged-dependent variable, the spatial lagged-dependent variables, and the endogenous control variables. Specifically:

$$B = \left[-\frac{\sigma^2_\eta + \sigma_{x\eta}\lambda}{\sqrt{NT}}tr(\Pi),\ -\frac{\sigma^2_\eta + \sigma_{x\eta}\lambda}{\sqrt{NT}}tr(W\Pi),\ -\sqrt{\frac{N}{T}}\frac{T-1}{T}\sigma_{z\eta}\right]',$$

where tr is the trace operator and σ^2_η is the variance of the error term η. The $1 \times K$ vectors $\sigma_{x\eta}$ and $\sigma_{x\eta}$ contain the expectations $E(X\eta)$ and $E(Z\eta)$, respectively. The $N \times N$ matrix Π is $(I - \Psi)^{-1}$, $\Psi = (\pi I + \rho W)$. To implement the estimator, we follow Korniotis (2010) and use a two step approach. In the first step, we obtain an initial estimate for ϕ that we use to obtain the value of the bias vector B. Then, in the second step we compute the bias corrected estimator $\hat{\phi}_c$.

Extension: Natural Disasters

In one of our tests, we instrument the spatial lagged dependent variable WY_{t-1} with WD_{t-1}, D being the scaled monetary losses from natural disasters. We extend the bias corrected estimator and build a new IV-inspired estimator. The new estimator is identical to $\hat{\phi}_c$ with only one difference. In the matrix $\tilde{Z}_{i,t-1}$, we replace $W_i Y_{t-1}$ with $W_i D_{t-1}$. Tracing the proofs in Korniotis (2010), one can show that now the bias related to the spatial lagged dependent variable is:

$$-\frac{tr(W'\Omega_D)}{\sqrt{NT}},$$

where Ω_D is the $N \times N$ variance-covariance matrix related to the scaled monetary losses from natural disasters D. It is important to allow cross-state correlations because natural disasters like hurricanes can affect more than one states. In the special case where the natural disasters are uncorrelated across states, the bias term is zero.

Note that the IV extension of the $\hat{\phi}_c$ estimator is based on the simplest instrumental variable estimator for linear regression models. For example, in the linear regression $Y = X\beta + \eta$, if X and η are correlated, the simplest IV estimator for β is $(Z^{'}X)^{-1}(Z^{'}Y)$, where Z includes the instruments for X. We use the simplest IV estimator as opposed to using the more involved two-stage least squares because this allows us to obtain closed-form solutions for the bias terms in the bias corrected estimator.

TABLE A.1
Results from Validation Tests

This table reports cross-sectional average estimates of time-series regression coefficients for the relation between portfolio stock returns or operating performance of firms not headquartered in state s and that of firms headquartered in state s. For each state, we form three distinct portfolios. The first portfolio contains all firms headquartered in the state (HQ Index). The second portfolio consists of firms that are not headquartered in the state but have significant economic interests in the state, i.e., firms for which the firm-state citation share is in the top 3 (EC). The third portfolio contains all firms that are neither headquartered nor have significant significant economic interests in the state (No HQ/EC). Next, we create state-level indices by either value-weighting (VW) or citation share-weighting (SW) the firms within the state. Finally, for each state, we estimate a time-series model and report the mean estimates. We estimate the regressions separately for EC and No HQ/EC portfolios and consider three firm-level measures: (i) raw monthly stock returns (see Columns (1) to (3)), (ii) quarterly sales divided by firm assets at the beginning of the quarter (see Columns (4) to (6)), and (iii) quarterly capital expenditure divided by firm assets at the beginning of the quarter (see Columns (7) to (9)). The sample period is from 1994 to 2010.

	RETURN (1-3)			SALES (4-6)			CAPEX (7-9)		
Portfolio:	EC	No HQ/EC	EC	EC	No HQ/EC	EC	EC	No HQ/EC	EC
Weighting Scheme:	VW	VW	SW	VW	VW	SW	VW	VW	SW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State HQ Portfolio	0.102	−0.019	0.322	0.298	−0.026	0.280	0.342	−0.031	0.335
	(5.88)	(−4.07)	(10.53)	(2.68)	(−1.72)	(5.02)	(4.08)	(−1.85)	(7.72)
Market	0.856	1.020	0.662	0.673	1.019	0.917	0.870	1.028	0.738
	(35.81)	(209.34)	(24.94)	(3.28)	(102.64)	(7.13)	(8.60)	(104.10)	(7.00)
SMB	−0.034	0.001	0.527						
	(−1.42)	(0.99)	(23.18)						
HML	0.0576	0.0011	0.1466						
	(1.66)	(1.02)	(4.97)						
UMD	−0.015	−0.001	−0.148						
	(−1.39)	(−1.71)	(−11.74)						
Num EC/HQ Firms	−0.005	0.000	−0.001	−0.042	0.000	−0.035	−0.003	−0.000	−0.001
	(−1.47)	(1.23)	(−0.41)	(−2.30)	(0.45)	(−2.14)	(−1.19)	(−0.94)	(−0.30)
Mcap EC/HQ Firms	−0.006	0.000	−0.004	−0.053	0.001	0.002	−0.001	0.000	−0.000
	(−6.80)	(4.50)	(−3.00)	(−6.84)	(3.69)	(0.51)	(−1.68)	(2.11)	(−0.11)
Avg R^2	0.723	0.999	0.753	0.639	0.997	0.531	0.561	0.997	0.553
Median R^2	0.730	0.999	0.797	0.694	0.999	0.543	0.578	0.999	0.535
N(State Time-Series)	50	50	50	50	50	50	50	50	50