Overlapping Real Asset Networks and Corporate Investment*

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ABSTRACT

This study shows how the interconnected real asset networks among corporations affect their corporate investment. We develop a theoretical model that predicts commonalities resulting from a firm's asset network will lead to higher optimal investment, and we empirically test these predictions using spatial econometrics and network methods. Controlling for both industry and headquarters co-investments, we find a 1% increase in the instrumented asset network co-investments relative to its long-term average is associated with a 0.35% increase in the typical firm's rate of investment. Although most prior research uses the headquarters locations of two firms as a proxy for geographic connectivity, we find that the geographic overlap of their assets (subsidiaries) is more important than headquarters connectivity. We further show that our findings are not driven by non-tradable goods and services sectors nor by firms whose subsidiary networks are tilted toward states that are expected to produce faster economic growth. Importantly, we find that our documented asset network effect prevails among firms with higher corporate real estate holdings, which can be pledged as collateral for debt financing. A 1% increase in the debt issuance of companies in a firm's asset network relative to its long-term average is associated with a 0.37% increase in a firm's debt issuance. Our findings are robust to alternative specifications and omitted variable tests. Overall, our findings have important implications for assessing the effects of the locational boundary of firms, their overlapping locational networks, and their peer effects on firm corporate financial policy decision-making.

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1 Introduction

The co-location of firm headquarters has been documented as a significant factor influencing corporate decision-making and economic activities (Dougal, Parsons, and Titman, 2015; Korniotis and Kumar, 2013; and LaPoint and Sakabe, 2021). However, as firms increasingly integrate technology and distant supply chains into their operations, tension emerges between the traditional benefits of headquarters co-location and the rising costs associated with maintaining a particular geographic presence.[1] This tension underscores a broader paradox of location, which carries critical implications for understanding the locational boundaries of firms, their interconnected geographic networks, and the corresponding impact on financial policy decisions. Corporate investment opportunities frequently exhibit correlations due to factors such as market trends, regulatory shifts, production inputs, and location. Consequently, a firm's investment decisions are often interdependent with those of other firms, particularly when exposed to shared fluctuations in investment opportunities—an occurrence referred to as investment commonalities. These investment commonalities are closely linked to peer effects (Grieser, Hadlock, LeSage, and Zekhnini, 2022), where product-market competitors influence a firm’s profitability, thereby leading to corporate policy choices that incorporate feedback from industry rivals. Notably, these peer effects transcend the mere co-location of headquarters, prompting an inquiry into the role that a firm’s broader locational network plays in shaping its financial policy decisions.

In this paper, we investigate the influence of firms’ real asset network co-location on corporate investment behavior. The literature has identified various types of investment commonalities (Bustamante and Frésard, 2021), and our focus is on those arising from a firm’s geographic connections to other firms’ real asset networks. Geographic overlaps within intra-firm networks—whether due to proximity of headquarters (headquarters commonality) or shared operational locations (asset network commonality)—bear significant implications for investment decisions. These implications are driven by endogenous interactions among firms and local economic agents, including demographic shifts, land use changes, and broader economic activity, all of which contribute to the economic vibrancy of specific locations. A pertinent example is the establishment of "Million Dollar Plants," where the productivity spillovers from new plants can significantly influence the investment decisions of existing nearby facilities (Greenstone, Hornbeck, and Moretti, 2010; Giroud, Lenzu, Maingi, and Mueller, 2024).[2]

[1] In the post-pandemic era, many workers are hesitant to return to the office and argue that the idea of a central office location (i.e., headquarters) is obsolete, especially when colleagues are based in other regions. (https://www.wsj.com/articles/its-not-my-responsibility-to-save-the-office-economy-901dafce). The rise of remote work, as well as rising interest rates, has led to increasing defaults and vacancies at high-end office buildings in central locations (Davis, Ghent, and Gregory, 2021; Gupta, Mittal, and Van Nieuwerburgh, 2022), but not other locations (Rosenthal, Strange, and Urrego, 2022).

[2] Appendix 2 depicts the key distinctions between Giroud et al. (2024) and this paper. The former highlights the importance of cross-plant spillovers through the asset network. The authors find that internal spillovers within a

Geographic investment commonalities have been traditionally studied either in isolation between pairs of firms or within networks of establishments confined to a single firm, often neglecting the broader geographic dispersion of such networks. The existing literature also underscores the role of "functional specialization" in shaping urban forms (Duranton and Puga, 2005; Davis and Henderson, 2008), where cities transition from sectoral specialization to functional specialization, thereby leading to the clustering of firm headquarters and establishments in specific urban areas (Bernile, Kumar, and Sulaeman, 2015). While previous research has predominantly focused on the impact of headquarter clustering on firm investments (Dougal et al., 2015), the effects of clustering within firms' asset networks have received insufficient attention. Emerging research, however, highlights the significance of disaggregation in firm linkages, with growing evidence on inter-firm effects originating from distant plants compared to within-firm establishment-level impacts (Greenstone et al., 2010; Giroud et al., 2024). Building on these insights, our paper delves into corporate co-investment effects from a disaggregation perspective, emphasizing the co-location of firms' real asset networks while also accounting for the influence of headquarters co-location. Importantly, our research provides new results on the increasingly complex interplay among geographic co-location, firm networks, and corporate investment decisions.

We develop a tractable theoretical model, independent of any functional form assumptions, to derive empirical predictions. Based on the implications of this theoretical framework, we conjecture that firms with establishments in the same location(s) are exposed to common fluctuations in local production input costs—including land values—holding everything else constant. To test the predictions of our theoretical model, we adopt a novel, hybrid use of spatial econometrics and network methods to examine the role of asset networks in determining firms' investment commonalities. Specifically, we augment standard corporate investment regression specifications with a spatially lagged element (Grieser et al., 2022) that allows us to quantify the effect on a firm *i*'s investment in year *t* of investments in year *t*-1 by firms—in any industry—whose assets are tilted toward the same locations as firm *i*. We refer to this "overlap" of asset locations as the "asset network co-investment" of two firms.

In our analysis, we first gauge the extent of overlap (clustering) of firms' establishments using publicly disclosed data on the names and locations of a firm's significant subsidiaries (Garcia and Norli, 2012; Bernile et al., 2015). The proportion of a firm's subsidiaries allocated to a particular location (*Subsid Share*) is used to create a spatially weighted matrix of all possible firm pairs in our sample. Second, we construct each firm's asset network co-investment as the weighted average investment made by firms that have subsidiaries in the same location(s) as the subject firm. Finally, we estimate the impact of asset network co-investment on firms' subsequent investment using the weighted averages of neighbors' investment as an instrumental variable in a two-stage least squares regression framework.

firm's boundary decay slowly over geographic distance. In contrast, we focus on whether a firm can internalize cross-plant spillovers both within and beyond its boundary.

Throughout our analyses, we control for both industry and headquarters co-investment, along with numerous other controls.

Our findings suggest that a 1% increase in the instrumented asset network co-investments relative to its long-term average is associated with a 0.35% increase in the typical firm's rate of investment. This result is similar to the estimated effect of the firms' industry network on investment. Further analyses reveal that the effect of headquarters networks on firm investment decays as firms' geographic complexity increases (proxied by the number of locations in which a firm has a physical presence). In sharp contrast, the effect of firms' asset networks on investment increases as firms' geographic complexity increases.

Importantly, firms that share a physical presence in geographical locations with other firms may be exposed to common fluctuations in local economic activity, which could affect the interpretation of our findings depending on the channel through which our asset network co-investment variable is thought to be affecting a firm's investment. To address these potential interpretation views, we test the extent to which firms in our asset network that produce goods and services consumed locally (i.e., non-tradeable goods) drive our findings. We also test the extent to which our instrumented asset network serves as a proxy for the transmission of local economic shocks across firms through overlapping asset networks. We show that our asset network co-investment results are only partially driven by non-tradable goods and services sectors (i.e., do not concentrate on non-tradeable goods and services). Similarly, our results are not driven by firms whose subsidiary networks are tilted toward states that are expected to produce faster economic growth. We further show that our results are robust to alternative specifications of *Subsid Share* and are unlikely to be the result of omitted variable bias. Finally, we show the asset network effect persists among firms with higher corporate real estate holdings, which can be pledged as collateral for debt financing. Importantly, a 1% increase in the debt issuance of companies in a firm's asset network relative to its long-term average is associated with a 0.37% increase in a firm's debt issuance—quantitatively similar to the effect of the asset network on firm investment.

Our paper contributes to three key strands of literature. First, our results reinforce the importance of peer effects in corporate financial policy decisions – specifically the peer effect of firms' real asset networks on corporate investment. Earlier research finds peer firms' decisions influence capital structure (Grieser et al., 2022), co-located headquarter investment (Dougal et al., 2015), valuation (Foucault and Frésard, 2014; Bustamante and Frésard, 2021), and market liquidity (Cespa and Foucault, 2014). We find that firms' real asset networks materially affect firm corporate investment. Distinct from prior studies, our findings also suggest that the asset network co-investment effect is likely driven by rising debt capacity rather than peer learning among corporate managers.

Second, our findings contribute to the literature on the collateral channel of fixed assets. Corporate real estate is generally a better form of loan collateral than equipment and intangible assets. Thus, an increase in the usage of CorpRE can enhance overall borrowing capacity (Cvijanović, 2014; Campello, Connolly, and Kankanhalli, 2021) that, in turn, leads to more investment (Chaney, Sraer, and Thesmar, 2012). A firm's cost of capital is also tightly linked to its use of real estate in the production process. Several prior studies show that real estate prices predict firm investment and argue that this relation is driven by real estate's value as loan collateral (Gan, 2007; Tuzel, 2010; Chaney et al., 2012; Tuzel and Zhang, 2017). In contrast to prior studies that use headquarters location as a proxy for the location of a firm's CorpRE, our findings demonstrate the importance of using a firm's real asset network to measure its geographic footprint.

Finally, the modeling approach we employ allows us to link production spillovers at the firm and the establishment levels (Greenstone et al., 2010; Giroud et al., 2024). Identification challenges may arise due to the reflection problem -- the tendency that the average behavior of a group influences the behavior of the individuals that comprise the group (Manski, 1993). Tackling the reflection problem requires richer modeling approaches. A pioneering work that addresses this problem in a corporate finance setting is Grieser et al. (2022). We advance their work by constructing peer weights using data on the geographic dispersion of firms' establishments as opposed to textual data on the product similarity of firms. Importantly, equipped with a novel spatial-gravity model, we mitigate concerns about endogenous site selection of establishments (and thus peer weights).

The rest of our paper proceeds as follows. Section 2 provides a theoretical model that hypothesizes the relationships between alternative forms of co-investments. Section 3 outlines our empirical modeling approach to the related hypotheses. Section 4 characterizes the data and sample we employed for the estimation. Section 5 displays our main findings. Section 6 concludes.

2 Conceptual Framework

We develop a simple theoretical framework to fix ideas and to guide our empirical analysis. Our model is particularly useful for framing and understanding the relevant co-investment spillovers at play based on production theory. The model we present does not rely on any standard functional form assumptions, and therefore the findings can be generalized to any technological specifications. Our key finding in this section is that a model of the firm's cost minimization problem implies a positive relation between a firm's optimal investment and other firms' headquarters locations, asset locations (subsidiaries), industry spillovers, and *Tobin's Qs*. Our subsequent empirical analyses test for the presence and magnitude of each type of spillover.

The theory behind our empirical tests is grounded in the literature on the production process and agglomeration, popularized by Duranton and Puga (2001) and Davis and Henderson (2008). In these models, a firm's output is a function of its capital stock and labor, along with a shift factor that represents a variety of forces, such as potential spillover effects from various types of co-investment. Many of these models are tests of "urban vibrancy" (Dougal et al., 2015).

2.1 A Model of Corporate Investment with Co-Investments

As previously noted, models of "urban vibrancy" are grounded in a production function framework. In the context of a problem where other firms' headquarters investments and subsidiary investments might spill over to enhance a firm's productivity, such a production function can be shown as:

$$Y = F(A_Y, INV, \overline{INV}\ N; X),$$
$$where\ A_Y \equiv [f(HQ\ Location\ CoINV, Asset\ Network\ CoINV)] \qquad (1)$$

In equation (1), A_Y is an exogenous agglomeration factor; N is the amount of labor employed; INV is the level of investment in a given time period; and $\overline{INV}$ is the firm's past investment levels, net of depreciation, which are in place in a given time period. $HQ\ Location\ CoINV$ is the average investment of firms that are headquartered in the same geographic jurisdictions but operate in different industries from the subject firm; $Asset\ Network\ CoINV$ is the weighted average investment of firms that have subsidiaries in the same geographic jurisdictions as the subject firm (see section 3.2); and X is a vector of exogenous control variables that may affect the firm's output, Y. A typical assumption is that F is strictly concave. In this formulation, greater $HQ\ Location\ CoINV$ or greater $Asset\ Network\ CoINV$ implies higher output for a particular firm since the first partial derivative of f with respect to the respective co-investment term is positive. This shift factor, A_Y, can lead to an increase in a firm's profits (or lower costs) due to the urban vibrancy that is associated with headquarters co-locations, or due to what we call "overlapping real asset networks."

The following assumptions are important stepping-stones for the model implications in Section 2.2 below:

- **Assumption 1:** Labor is highly productive, given the levels of current and lagged investments.
- **Assumption 2:** Higher levels of investment improve the productivity of labor.
- **Assumption 3:** Greater $HQ\ Network\ CoINV$ or greater $Asset\ Network\ CoINV$ leads to higher marginal product of INV.
- **Assumption 4:** Greater $HQ\ Network\ CoINV$ or greater $Asset\ Network\ CoINV$ leads to higher marginal product of N.
- **Assumption 5:** The effect of greater $HQ\ Network\ CoINV$ or greater $Asset\ Network\ CoINV$ on the marginal product of N is small relative to the effect of greater $HQ\ Network\ CoINV$ or greater $Asset\ Network\ CoINV$ on the marginal product of INV.

Assumptions 1 and 2 are artifacts of the current state of technology in the U.S., compared with developing countries. The U.S. is the context for our empirical analysis below.

Assumptions 3 and 4 are intuitive in that each of these agglomeration factors complement the productivity of investment, for a given level of N. But given the complexity of the production relationships implied by the firm's optimization problem and the investment adjustment cost function described below, it is not apparent a priori whether Assumptions 3 and 4 directly imply a positive relationship between a firm's optimal investment and $HQ\ Network\ CoINV$ or $Asset\ Network\ CoINV$.

Assumption 5 is based on the notion that in a highly industrialized country such as the U.S., agglomeration due to co-investment is more productive with respect to investment goods than with respect to labor. This is likely to hold in nonservice-related industries, which are primarily the focus of this paper.

An alternative approach to modelling the effects of co-investment that is appealing in our context is the cost minimization problem. In contrast to the production function approach, the cost function approach enables us to bring in Tobin's Q as a determinant of optimal investment, as shown below and in Appendix 6. Duality theory (Diewert, 1982) implies the same choice of optimal investment will be made whether the firm minimizes costs or maximizes profits. The analogous total cost function can be written as:

$$C = wN^{*} + P_{INV}INV^{*} \tag{2}$$

where C represents the firm's (long-run) total production costs, w is the average wage rate, N^{*} is the optimal amount of workers, INV^{*} is the firm's optimal investment at a given point in time, and P_{INV} is the price of INV^{*}.[3,4]

Dougal et al. (2015) find empirically that $HQ\ Network\ CoINV$ significantly impacts a firm's investment, whereas we also examine the extent to which $Asset\ Network\ CoINV$ affects a firm's investment while controlling for $HQ\ Network\ CoINV$. We demonstrate below that a cost minimizing firm's optimal investment can be expressed as a function of $Asset\ Network\ CoINV$, $HQ\ Network\ CoINV$, $Industry\ CoINV$, and $Tobin's\ Q$. An attractive feature of this framework is that we can explore whether higher $Asset\ Network\ CoINV$ and/or higher $HQ\ Network\ CoINV$ lead to lower total costs.

One aspect of the investment problem that the cost-minimizing firm needs to consider is the rate of capital accumulation. Hayashi (1982) presents a general capital accumulation equation by incorporating an adjustment cost (or installation cost) embedded in the function ψ, as the following modified physical capital (K) accumulation equation:

$$\dot{K} = \psi(INV, K). \tag{3}$$

One might hypothesize that a firm's adjustment costs are lower (and in turn, capital accumulation is greater) when there is greater investment by other firms in the same industry, due to the possibility of knowledge spillovers. Also, in our model the capital stock is essentially a function of past levels of INV (net of depreciation). Therefore, we write:

[3] See Cohen and Paul (2005) for a cost function setup similar to equation (2).

[4] We assume the typical firm's manager(s) make optimal decisions in each time period, *t*. For simplicity, time subscripts are suppressed in this model section and a static optimization problem is assumed. The general comparative statics implications of the model would carry over in a dynamic optimization process where the firm optimizes a forward-looking problem in each time-period.

$$\dot{K} = \psi(\alpha, INV, \overline{INV}) \qquad (3')$$

where $\alpha \equiv Industry\ CoINV^{-1}$, and $\overline{INV}$ is defined as a function of lagged investments (which, in conjunction with INV, represents the average size of the firm). In this situation, α is a shift factor for the adjustment cost function, so that more investments by all firms in the industry lowers the adjustment costs, and enhances the capital accumulation, of each particular firm.

- **Assumption 6:** The first partial derivative of ψ with respect to INV (i.e., ψ_{INV}) is positive, and $\psi_{INV,INV} < 0$.
- **Assumption 7:** Greater $Industry\ CoINV, \alpha,$ shifts the adjustment cost function, ψ, downward.

Assumption 6 is based on assumptions made by Hayashi (1982), which imply a strictly concave investment adjustment cost function. Once again, the sign and statistical significance of the relationship between α and a firm's optimal investment is a testable hypothesis; however, if one believes that greater $Industry\ CoINV$ leads to lower adjustment costs, this should leave greater resources for a firm to increase its INV.

Assumption 7 basically states that greater industry network co-investment lowers the total adjustment costs of installing additional investment, as well as lowers the marginal costs of installing investment.

To develop a reduced form that can shed light on testable model implications, we assume in each period (e.g., year) the typical firm minimizes the cost of producing a given level of output, subject to its rate of capital accumulation. In other words, the firm's optimization problem in year t is to choose INV and N to minimize C subject to the capital accumulation equation (net of adjustment costs and depreciation) and a given level of Y. More formally, the cost minimization problem's Lagrangian, $\mathcal{L}$, at a particular point in time for a representative firm, can be written as follows:

$$min_{N,INV}\, \mathcal{L} = [wN + P_{INV}INV] + \lambda[\dot{K} - \psi(\alpha, INV, \overline{INV})] + \gamma[Y - F(A_Y, INV, \overline{INV}, N)] \qquad (4)$$

Recall that the agglomeration factor is denoted by the vector A_Y. We assume A_Y is an increasing function of $HQ\ Network\ CoINV$ and $Asset\ Network\ CoINV$. In other words, a firm's production may be augmented by investment by firms in either its headquarters network or its asset network. A priori, it is not clear under what conditions either of these has a positive effect on optimal investment, or which of these — $HQ\ Network\ CoINV$ or $Asset\ Network\ CoINV$—has a larger effect on optimal investment.

As we demonstrate in Appendix 6, the optimal level of INV is a function of $Q, HQ\ Network\ CoINV, Asset\ Network\ CoINV, \alpha, X$; and other exogenous parameters:

$$INV^* = h(Q, A_{HQ}, A_A, \alpha, X;\ P_{INV}, w, Y, K, \gamma, \delta) \quad (5)$$

where $A_Y \equiv [A_{HQ}, A_A]$ and A_{HQ} is defined as $HQ\ Network\ CoINV,$ and A_A is defined as $Asset\ Network\ CoINV.$

Finally, there is one more important Assumption, despite the fact that it should always hold in the long run:

Assumption 8: Both the price of investment and the shadow price of investment are strictly positive.

Therefore, given the above Assumptions and under some additional assumptions, it can be demonstrated that the following propositions hold (see Appendix 6 for the proofs of each proposition):

Proposition 1: ${\partial INV^*}/{\partial A_{HQ}} > 0.$

Proposition 2: ${\partial INV^*}/{\partial A_A} > 0.$

Proposition 3: ${\partial INV^*}/{\partial A_A} > {\partial INV^*}/{\partial A_{HQ}}$ if $F_{INV,A_A} > F_{INV,A_{HQ}}$, $F_{N,A_A} > F_{N,A_{HQ}}$, and $F_{A_A} < F_{A_{HQ}}$.

Proposition 4: ${\partial INV^*}/{\partial \alpha} > 0.$

Proposition 5: ${\partial INV^*}/{\partial Q} > 0.$

2.2 Model Implications and Empirical Predictions

Propositions 1-5 from our modelling framework imply several empirical predictions. Our first three predictions focus on headquarters and asset network co-investment (or spillover) effects, while our fourth prediction relates to industry network co-investment effects. Specifically:

Prediction 1: Greater asset network co-investment, or greater headquarters network co-investment, leads to higher optimal firm investment. These predictions are based on Propositions 1 and 2.

Prediction 2: The asset network co-investment effect on firm investment is larger than the headquarters co-investment effect on firm investment. This empirical prediction is based on Proposition 3.

Prediction 3: Greater industry network co-investment, α, implies higher optimal firm INV^*. This model prediction comes from Proposition 4.

Prediction 4: Optimal firm investment is greater when the firm's Q is higher. Proposition 5 implies this model prediction.

We take these predictions to the data and empirically test the signs and significance of these INV^* covariates. These statistical tests are the primary focus of the following empirical section.

3 Empirical Strategy

3.1 Traditional Investment Model

Based on the framework established in section 2, a traditional investment model (assuming zero co-investment) can be expressed as:

$$INV_{i,t} = \alpha_i + \rho Q_{i,t-1} + \beta X_{i,t-1} + u_{i,t} \tag{6}$$

where $INV_{i,t}$ is the rate of investment made by firm *i* in year *t*. *X* represents a vector of lagged predictors such as firm size and cash flow. Q theory suggests that the marginal effect of *Q*, measured by ρ, on investment, ceteris paribus, should be positive (Hayashi, 1982). Other control variables are discussed in Section 4.

3.2 Firm Headquarters and Investment Commonality

Prior research underscores the importance of considering how investments made by firms headquartered in the same market covary even if most of the firms operate in different industries (e.g., Dougal *et al.*, 2015). Therefore, we enhance equation (6) by including lagged investments made by economically relevant peer firms:

$$\begin{aligned} INV_{i,j,l,t} = \alpha_{i,j,l} &+ \gamma_1 Industry\ Network\ CoINV_{-i,j,t-1} \\ &+ \gamma_2 HQ\ Network\ CoINV_{-j,l,t-1} + \rho Q_{i,t-1} + \beta X_{i,j,l,t-1} \\ &+ u_{i,j,l,t}. \end{aligned} \tag{7}$$

$Industry\ CoINV_{-i,j,t}$ represents the mean aggregate investment of firms that operate in the same industry (*j*) as the subject firm *i*. $HQ\ Network\ CoINV_{-j,l,t}$ captures the average investment of firms in different industries (*-j*) that are headquartered in the same geographic jurisdiction *l* as the subject firm i in year *t*-1. $HQ\ Network\ CoINV_{-j,l,t}$ is constructed to capture the interactions of firms whose headquarters are co-located. These interactions potentially create "urban vibrancy," including knowledge and technology spillovers between neighboring firms and workers (Dougal et al., 2015). Industry (SIC4) and year fixed effects are included in the investment specification.

Our theoretical framework of optimal investment includes the potential roles played by headquarters and industry networks; however, it also models the role overlapping asset networks play in determining firm investment. Empirically, we therefore augment equation (7) with a spatially lagged element (Grieser et al., 2022) that allows us to quantify the effect on firm *i*'s investment in year *t* of investments by firms—in any industry— in year *t*-1 whose assets overlap with the locations (markets) of firm *i*. Formally, we estimate the following Spatial Autoregressive Regression (SAR) model:

$$INV_{i,j,l,a,t} = \alpha_{i,j,l,a} + \rho Asset\ Network\ CoINV_{-i,a,t-1} + \gamma_1 Industry\ Netwotk\ CoINV_{-i,j,t-1} + \gamma_2 HQ\ Network\ CoINV_{-j,l,t-1} + \rho Q_{i,t-1} + \beta X_{i,j,l,t-1} + u_{i,j,l,t} \quad (8)$$

where *Asset Network CoINV*$_{-i,a,t-1}$ represents the weighted average investment made by firms that have subsidiaries in the same state(s) *a* as the subject firm *i* in year *t*-1. In spatial econometric terms, the weight applied to firm -*i*'s investment in year *t*-1 that is headquartered or has a subsidiary in the same state as firm *i* can be expressed as $W_{i,-i,t-1}INV_{-i,t-1}$, where *W* is a spatial weights matrix that captures the extent to which the locations of firm -*i*'s subsidiaries overlap with firm *i*'s subsidiaries. We refer to this as the firm's "subsidiary share" at time *t*.

A key to the construction of $Asset\ Network\ CoINV_{-i,a,t-1}$ is the construction of the spatial weights matrix, *W*.[5] For firm *i* in year *t*, we calculate its subsidiary share, *Subsid Share*$_{i,s,t}$, as the proportion of its subsidiaries located in state *s* at the beginning of year *t*. We then aggregate for firm *i* its *Subsid Share*$_{i,s,t}$ across all states *a* in which both firms *i* and -*i* have subsidiaries. We repeat the same process for firm -*i*. The spatial weight for firms *i* and -*i*, $\phi_{i,-i,t}$, is defined as the minimum of the aggregate *Subsid Share*$_{i,a,t}$ and *Subsid Share*$_{-i,a,t}$.[6] We have a separate weights matrix for each year *t*, denoted as W_t, so the dimensions of the weight matrix is N_t by N_t. N_t is the total number of firms with data on subsidiaries available from WRDS in year *t*. Finally, we row normalize $\phi_{i,-i,t}$ to obtain the *i,-i* element of the spatial weights matrix:

$$w_{i,-i,t} = \frac{\phi_{i,-i,t}}{\sum_{N_t-1} \phi_{i,-i,t}} \quad (9)$$

where i=1, 2,…,N_t. These yearly matrices, W_t, are stacked over all periods, *t*=1, 2,…, T, to yield our final spatial weights matrix, *W*.

Endogeneity issues might arise if $Asset\ Network\ CoINV_{-i,a,t-1}$ and $INV_{i,j,l,a,t}$ are correlated with omitted explanatory variables. However, because the spatial weights matrix, *W*, is row-normalized, we can apply Gershgorin's Theorem (Horn and Johnson, 1985; Kelejian and Prucha, 1998; Kelejian and Prucha, 2010) and assume the spatial lags of our explanatory variables, or *Asset* $X_{i,t-1}$ (e.g., firm size and Tobin's Q are a valid instrument for *Asset Network CoINV*$_{-i,a,t,l-}$ This is because the lagged explanatory variables , and thus the expected *Asset Network CoINV,* are by construction uncorrelated with the residual of the subject firm, *u*. We therefore estimate equation (8) in a 2sls manner. The first-stage regression is:

$$Asset\ Network\ CoINV_{-i,a,t} = \beta Asset\ X_{i,t-1} + \epsilon_{i,t} \quad (10)$$

In the second stage regression, we estimate equation (8) with the instrumented *Asset Network CoINV* from equation (10). Our coefficient of interest is ρ.

[5] In Appendix 5, we present a simplified numerical example of constructing a spatial weights matrix for three firms that have subsidiaries across four states.

[6] Our results are qualitatively similar if we use alternative specifications such as maximum weights.

4 Data and Sample Construction

We start with all listed U.S. firms included in the CRSP/Compustat Merged Database (CCM) from 1998 to 2019. The WRDS Company Subsidiary Data became available in 1998 and thus dictates the beginning of our sample period. We delete observations with incomplete financial information. We also exclude firm years with incomplete information from Compustat on historical headquarters addresses or operation segments.[7,8] Our initial sample contains 62,767 firm-year observations for 6,464 listed firms.[9]

We merge this sample with data obtained from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, Refinitiv (formerly Thomson Reuters), Ken French's Data Library, and Hoberg-Phillips' Data Library to obtain several variables not available from CCM. Yearly data on the name and location (state) of each subsidiary are sourced from SEC filings with Exhibit 21 (WRDS Company Subsidiary Data), including 10-K, 10-Q, 8-K, and others, which are available through SEC EDGAR. Exhibit 21 provides a detailed list of the names and locations of a firm's significant subsidiaries across the country and around the world (Dyreng, Lindsey, and Thornock, 2013). Subsidiary data allow us to measure a firm's geographic footprint and thus the extent to which its assets overlap with other firms. We further augment subsidiary data with data on yearly state population and the coordinates of state centroids from S&P Global Geographic Intelligence using the Federal Information Processing Standards (FIPS) of a state. These data are used to estimate the spatial gravity model specified below in Equation (12).

Refinitiv provides quarterly reports on the common stock holdings of 13F institutions. To construct our industry network co-investment variable, we translate Standard Industrial Classification (SIC) codes into the 12 industries classified by Fama and French (1997).[10] Finally, as a robustness check, we also measure the extent to which a firm's business operations overlap with others using 10-K text-based firm-by-firm pairwise similarity scores obtained from the Hoberg-Phillips Data Library. The merging of these various data reduces our final regression sample to 42,988 firm-year observations for 5,742 unique firms. Summary statistics are presented in Table 1; variable definitions are contained in Appendix 1.

[7] Firms not headquartered in the U.S. are also excluded from our analysis.
[8] Operational segments include geographic segments and business segments classified by a firm. We may not know what those segments are because we only have a masked ID for them. We use these data to calculate the extent of concentration of a firm's operation.
[9] Results are qualitatively similar if we exclude financial firms and utilities (i.e., those with SIC 4900-4999 or 6000-6999).
[10] Fama-French 12 industries include (1) Consumer Nondurables, (2) Consumer Durables, (3) Manufacturing, (4) Energy – Oil, Gas, and Coal Extraction and Products, (5) Chemicals, (6) Business Equipment – Computers, Software, and Electronic Equipment, (7) Telephone and Television Transmission, (8) Utilities, (9) Wholesale, Retail, and Some Services, (10) Healthcare, Medical Equipment, and Drugs, (11) Finance, and (12) Other.

4.1 Dependent Variables

We use yearly capital expenditures (CAPEX) divided by lagged total assets (L.AT) to proxy for the yearly rate of investment, *INV*, of a particular firm (Dougal et al., 2015).[11] *INV* in our sample has a mean (median) of 5.40% (3.35%).[12] Next, we turn to sources of financing. We focus on *net* debt issuance (*DEBT ISS*) because firms owning real estate in the same markets as other firms tend to experience common fluctuations in their ability to raise debt (Chaney et al., 2012). We define *DEBT ISS* as the sum of the changes in total long-term debt (DLTT), debt due in one year (D.D.), and notes payable (N.P.), divided by total assets (AT). During our 1998-2019 sample, firms had an average (median) *DEBT ISS* of 5.93% (0.08%).[13]

4.2 Headquarters and Asset Locations

We first obtain each firm's current headquarters location from the Compustat database (current addresses). Since subsidiary data contain the state location of subsidiaries, we only require the headquarters state (*state*) to be non-missing. We then identify any headquarters relocations using Compustat Snapshot and replace where appropriate the current address with the address prior to relocation.

Finally, we calculate subsidiary share as the number of a firm's subsidiaries located in a particular state in a given year divided by the total number of its subsidiaries across all U.S. states in that year. The mean (median) subsidiary share is 19.1% (6.5%).

Panels A and B of Figure 1 display heatmaps of headquarters locations at the state level at the beginning (1998) and end (2019) of our sample period. In each year, we calculate the percentage of firms headquartered in each state and then sort the states into quintiles based on this percentage. Darker shading indicates states with relatively more corporate headquarters. In both years, for example, Texas is among the 10 states with the highest percentage of firms headquartered there; North Dakota is a state with a low percentage of headquartered firms. A comparison of Panels A and B reveals that the states in which firms are headquartered have changed little from 1998 to 2019.

Panels C and D of Figure 1 display heat maps of subsidiary shares for 1998 and 2019. We again sort states into quintiles based on the (simple) average of each sample firm's subsidiary share (percentage) in that state. In both years, Florida is among the 10 states with the highest percentage of the typical firm's subsidiaries. A comparison of Panels C and D reveals that the states in which firms have a high percentage of subsidiaries vary more over time than their headquarters location. For example, Wisconsin, Colorado, and Minnesota become less important as subsidiary locations, whereas Utah, Iowa, and Ohio have a higher percentage of

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[11] Our results are robust to alternative definitions of the numerator, such as property, plant, and equipment.

[12] Dougal et al. (2015) documented a mean (median) INV for industrial firms of 7% (5%) in their 1997-2009 sample.

[13] According to Dougal et al. (2015), the mean (median) *DEBT ISS* of industrial firms was 8% (1%) during 1997-2009.

the typical firm's subsidiaries in 2019 than in 1998. Overall, Figure 1 provides evidence that the geographic footprints of firms' activities are more dynamic than headquarters locations.

In panel A of Figure 2, we present a comparison between headquarters networks and asset networks using 30 firms randomly drawn from our sample in 2019. The green ties (connections) indicate pairs of firms headquartered in the same state. The gray lines connect firm pairs with subsidiaries in the same state. The figure clearly reveals much more connectivity among subsidiaries (assets) than among headquarters locations.

In Panel B of Figure 2, we report *Closeness* centrality statistics for the asset network and the headquarters network for the 5,742 firms in our sample in 2019.[14] The centrality of the asset network exceeds the centrality of the headquarters network, and the difference is highly significant. Figure 3 presents additional evidence of the geographic dispersion of subsidiaries using two firms in our sample—Pfizer Inc. (Panel A) and Lumen Technologies Inc. (Panel B). Although headquartered in New York, Pfizer has subsidiaries in 12 states, including California and Florida. Louisiana-based Lumen Technologies has subsidiaries in 34 states.

Although most prior research uses the headquarters locations of two firms as a proxy for geographic connectivity, Figures 2 and 3 suggest that the geographic overlap of their assets (subsidiaries) may be more important than headquarters connectivity.

4.3 Measurement of Q

Standard investment theory posits that the rate of investment is a function of a firm's investment opportunities. *Tobin's Q*, which in theory equals the market value of a company's assets divided by the replacement cost of its assets, is typically used as a proxy for a firm's investment opportunities. Although the market value of a firm's publicly traded stock is readily available, the market value of the firm's liabilities and the replacement cost of its underlying assets are critical to the measurement of *Tobin's Q* and must be estimated. Traditionally, *Tobin's Q* does not incorporate the opportunities associated with intangible investments (e.g. Research & Development). Crouzet and Eberly (2023) find that intangible capital has grown as a share of investment and assets over the recent decades. This paradigm shift towards intangibles might cause physical investment to be low relative to valuations, resulting in an underestimation of the true stock of assets and thus overestimating a firm's incentive to invest in physical capital. Conversely, knowledge spillovers from intangible investments may produce significant externalities for peer firms, possibly leading to an underestimation of the

[14] Closeness centrality represents how close is a firm (on average) from all other firms within the asset network (Grund and Hedström, 2015). Specifically, the closeness of a firm *i* equals the inverse of the number of steps (on average) it takes a firm to reach all other firms:

$$Closeness_i = \frac{1}{\frac{1}{N-1}\sum_{j=1}^{N} L_{ij}}$$

Where *N* is the total number of firms in the network. L_{ij} is the minimum number of steps (i.e., shortest path between two firms) it takes firm *i* to reach firm *j*, $j \neq i$.

sensitivity of a firm's investment to *Tobin's Q*. Peters and Taylor (2017) propose an alternative to traditional Q (hereafter referred to as *PTQ*) that does incorporate intangibles.[15]

In addition to using the co-investment of peers in the firm's asset network ($Asset\ Network\ CoINV_{-i,a,t}$) to inform investment decisions, a firm's management may also obtain information from movements in the stock prices of peer firms in its asset network. This is because firms with overlapping geographic footprints (subsidiaries) may be subject to correlated shocks to fundamentals. Moreover, the asset network co-investment effect we seek to measure may be correlated with the real effects of shocks to the financial markets (Foucault and Fresard, 2014, 2019, Leary and Roberts, 2014). To address this potential omitted variable bias, we construct for each firm a time-varying, geographically weighted, measure of the aggregate valuation of firms that are connected to the subject firm in the asset network (*Asset Network Q*).

The mean and median of *Tobin's Q* (*PTQ*) are 1.61 and 1.17 (1.34 and 0.76), respectively. Dougal et al. (2015) show that, during 1997-2009, the mean and median of *Tobin's Q* were 1.62 and 1.02, respectively. The untabulated pairwise correlations between *PTQ* and *Tobin's Q* and *INV* are 0.04 and 0.12, respectively, which are statistically significant at the 1% level.

4.4 Other Investment Predictors

In addition to *Tobin's Q*, empirical research typically augments investment sensitivity regressions with firm cash flows (e.g., *EBITDA/AT*), which might contain information about marginal profitabilitiy or financial constraints.[16] We also measure a firm's geographic and sector focus (*GEOHHI* and *TypeHHI*) by constructing Herfindahl Indexes using data on the U.S. states in which the firm invests and the SIC segments in which it operates. Firms that diversify investments by state or by industry may have a less transparent asset base, firm structure, and higher management and financing costs than their more focused peers. This may subsequently lead to a lower rate of investment (Lamont and Polk, 2001; Lang and Stulz, 1994). We also construct a dichotomous variable that indicates whether a firm operates outside of the U.S. (*MNC*). Finally, we construct an alternative proxy for industry network co-investment, *H.P. Industry Network Co-INV*, using firm-by-firm similarity scores developed by Hoberg and Phillips (2016) based on the same weighting methodology detailed in Section 3.2.

Other control variables that enter our investment commonality analysis include lagged values of firm size (*SIZE*), leverage (*Leverage*), institutional ownership (*InstOwn*), and the book value of real estate (buildings and capital leases) divided by the number of employees (*RER*). Except for *Leverage*, these variables are likely associated with better access to capital markets and more transparency; thereby enhancing firm investment.

[15] Specifically, Peters and Taylor (2017) estimate the replacement cost of firms' intangible capital by accumulating past investments in R&D and SG&A. The Total Q, therefore, captures firms' investment opportunities better than other popular Tobin' Q proxies.

[16] Erickson and Whited (2000) argue that the importance of cash flow found in some previous investment research may be an artifact of the measurement error.

5 Findings

5.1 Baseline Results

Our baseline regression results are reported in Table 2. Industry (4-digit SIC) fixed effects and year fixed effects are included in all specifications. Standard errors are clustered at the industry-year level. The first column in Table 2 presents the results for estimating Equation (7). Consistent with Dougal et al. (2015), we find that both industry and headquarters network co-investment are positively associated with a firm's investment. The coefficient estimate on industry network co-investment is 0.413 (*t*-stat: 4.30), which is similar to the estimate of 0.503 (*t*-stat: 3.43) reported by Dougal et al. (2015). In terms of economic significance, a 1% increase in industry network co-investment relative to its long-term average—say, from 6% to 7%—would lead to a 0.41% increase in a typical firm's annual rate of investment. The magnitude of the coefficient estimate on headquarters network co-investment is smaller but still significant at 1% level. The estimated coefficients on our control variables have the expected signs. For instance, both *Cash Flow* and *Tobin's Q* are positively associated with firm investment because they provide information about a firm's investment opportunities (Hayashi, 1982; Poterba and Summers, 1988; Alti, 2003). In contrast, investment is negatively related to firm size and the use of leverage.

In column (2), we report the results obtained from estimating our Spatial Autoregressive Regression (SAR) model (Equation (8)) with a 2SLS approach. We drop $HQ\ Network\ CoINV$ from the specification and include our instrumented asset network co-investment variable (*IV Asset Network*). Our second-stage regression results reveal that the estimated coefficient on asset network co-investment is positive and highly significant.[17] However, the estimated coefficient on *Industry Network CoINV* remains positive and significant at the one percent level; that is, the mean aggregate investment of firms that operate in the same industry as the subject firm continues to predict the subject firm's investment when controlling for the firm's asset network co-investment.

In column (3), we display the results obtained when we include *IV Asset Network*, *HQ Network,* and *Industry Network co-investment* in the two-stage SAR regression. Asset network co-investment continues to predict firm investment. In fact, the estimated coefficient on *IV Asset Network* co-investment increases from 0.259 in column (2) (*t*-stat: 3.40) to 0.372 (*t*-stat: 4.26). A 1% increase in asset network co-investment relative to its long-term average would lead to a 0.35% increase in the typical firm's rate of investment. The estimated coefficient on *Industry Network* co-investment increases from 0.346 (*t*-stat: 10.32) to 0.399 (*t*-stat: 4.20) and remains highly significant. A 1% increase in industry network co-investment is associated with a 0.40% increase in a typical firm's rate of investment. However, the estimated coefficient on *HQ Network* co-investment cannot be distinguished from zero. The coefficient estimates on our three "network" variables are little changed when all three are included in the specification.

[17] The results of estimating our first-stage regression (Equation (10)) are reported in Appendix 3.

In summary, the co-investment of companies in a firm's headquarter network does not explain the firm's rate of investment when controlling for the firm's industry network and investment of companies in the firm's asset network. Our results are qualitatively similar when we replace *Tobin's Q* with Peters and Taylor's Total Q (*PTQ*). Formal statistical diagnostic tests (e.g. first-stage F-statistics) demonstrate the validity of the spatially lagged independent variables as instruments. Overall, these findings call into question the use of a firm's headquarters location as the sole proxy for its geographic footprint.[18]

5.2 Geographic Concentration and Headquarters Networks

To better understand the relation between asset networks and headquarters networks, we refine our measurement of a firm's asset network. For firms with geographically focused operations, its headquarters location may be an adequate proxy for the geography in which a firm operates (García and Norli, 2012; Tuzel and Zhang, 2017). However, for firms such as Lumen Technologies, with subsidiaries in 34 states, its headquarters location in Louisiana reveals very little about the geography of its economic interests.

To examine the rate at which the influence of a firm's headquarters network decays with geographical dispersion in our investment regressions, we classify firms as geographically concentrated if they have subsidiaries in less than or equal to two, three, or four states, respectively. In our second-stage investment regressions, we interact *HQ Network CoINV* with a dummy variable (*CONC*) that indicates a geographically focused firm.

In the results reported in the first column of Table 3, the concentration dummy variable is set equal to one if the firm has subsidiaries in no more than two states (including its headquarters state). The estimated coefficient on *HQ Network CoINV* is near zero. However, the coefficient estimate on *HQ Network x CONC* is positive and marginally significant. This indicates that a firm's headquarters network (location) is related to its investment, while controlling for its asset network effect, if the firm operates in no more than two states. However, the coefficient estimate on the interaction term is insignificant if the firm operates in more than two states (columns (2) and (3)). Thus, the influence of a firm's headquarters network dissipates rapidly as the number of states in which the firm has a physical presence increases. In contrast, the magnitude of the point estimate on *IV Asset Network Co-INV* increases slightly in magnitude and significance across the three specifications reported in Table 3.

5.3 Tradable versus Non-Tradable Industries

Firms that share a physical presence in a geographical location(s) with other firms may be exposed to common fluctuations in local economic activity. However, the degree to which

[18] In contrast to Dougal et al. (2015), we define co-headquartered firms based on their headquarters state rather than their economic area (EA) because the subsidiary data are available at the state level. One might expect the magnitude of the headquarters network co-investment to slightly increase if we define co-headquartered firms based on their EAs, which might subsume a portion of the asset network co-investment effect. However, by comparing columns (2) and (3), we find that excluding the headquarters network co-investment would bias the asset network co-investment effect downward, not upward.

fluctuations in a local economy matter to a firm with exposure to that market may depend on the extent to which the firm produces goods and services that are consumed in that local market instead of being exported to other distant locations. Firms that produce goods and services that are typically consumed where produced (e.g., many retail goods and the services sector) are often classified as "non-tradable" firms; in contrast, firms whose output is likely to be exported to other regions and countries are classified as firms that produce "tradable" output. The results presented in Tables 2 and 3 provide evidence that firm *i*'s investment in year *t* is strongly associated with investments in year *t*-1 by firms whose assets are tilted toward the same locations as firm *i*. However, this overlap (clustering) of asset locations may matter more if firm *i* tends to produce non-tradeable goods and services (i.e., those for which the demand for, and cost of, is more closely tied to the locations in which the services are produced).

Recognizing the importance of understanding how geographic concentrations (clusters) of industries--related by knowledge, skills, inputs, demand and/or other linkages--affect firm decision-making and outcomes, several recent papers have developed algorithms to classify industries into relevant clusters, including tradable and non-tradable industries and firms (Barkai and Karger, 2020; Bems, 2008; Delgado et al., 2016)). We base our classification of tradable versus non-tradable sectors on Delgado et al. (2016).

To examine the extent to which our asset network results are driven by non-tradable firms, we re-estimate our SAR model of a firm's rate of investment after augmenting the specification with a dichotomous variable, *Nontraded*, which is set equal to one if the firm operates primarily in a non-traded industry. In the results reported in column (1) of Table 4, we also report the estimated coefficient on a variable that captures the interaction between our instrumented asset network co-investment variable and *Nontraded* (*IV Asset Network x Nontraded*). The estimated coefficient on *Nontraded* is negative and significant at the 10% level, providing weak evidence that firms producing goods and services that tend to be consumed locally have lower rates of investment. In addition, the estimated coefficient on *Industry Network* co-investment remains positive and highly significant; however, firms' *HQ Network* co-investment does not help to explain rates of investment.

The estimated coefficient on the main variable of interest, *IV Asset Network x Nontraded*, is positive and significant at the 5% level; that is, the effect of a firm's asset network on investment tends to be even more pronounced among non-tradable firms. However, the estimated coefficient on *IV Asset Network* remains positive and highly significant. Thus, the effects of firms' asset networks on investment are not subsumed by their classification as a non-tradable (versus a tradable) firm.

In the results reported in column (2) of Table 4, we replace *IV Asset Network x Nontraded* with the interaction between the firm's headquarters network and *Nontraded* (*HQ Network x Nontraded*). The estimated coefficient on *Nontraded* is negative and significant at the 5% level. However, the coefficient on *HQ Network* remains insignificant, although the coefficient on *HQ Network x Nontraded* is positive and significant at the 5% level. This result suggests that firms' headquarters networks matter only among firms whose headquarters networks include firms that primarily produce non-tradeable (locally consumed) goods and services. Importantly, the strong statistical and economic significance of the positive coefficient on *IV Asset Network* is unaltered by the inclusion of *HQ Network x Nontraded* in the specification.

We next replace *HQ Network x Nontraded* with *Industry Network* x *Nontraded*; these results are reported in column (3) of Table 4. The estimated coefficient on *Nontraded* remains negative and significant at the 10% level. The coefficient on *Industry Network* remains positive and highly significant, reinforcing the result that a firm's industry network tends to matter more than its headquarters network. The estimated coefficient on *Industry Network x Nontraded* is positive and significant at the 10% level, suggesting that the positive influence of a firm's industry network on investment is magnified (marginally) among non-traded firms. Once again, the strong positive relation between *IV Asset Network* and firm investment is unaltered by the inclusion of *Industry Network x Nontraded* in the specification.

Overall, these results suggest that, while the headquarters network investment effects are concentrated among firms that produce nontradable goods and services sectors, both the asset network and the industry network effects are only partially driven by the nontradable goods and services sectors.

5.4 Local and National Economic Shocks

Our theoretical model suggests a prominent role for firms' asset networks in their investment decision-making. This role is confirmed by the empirical results presented in Tables 2 and 3, as well as by the "nontraded" results displayed in Table 4. However, the interpretation of the consistently positive coefficient on *IV Asset Network* co-investment may depend on the channel through which the asset network co-investment variable is thought to be affecting a firm's investment. If the lagged asset network co-investment variable is itself causing a change in a firm's investment, our instrumental variable captures this causality.

Another plausible explanation, however, is that the positive coefficient on *IV Asset Network* co-investment serves as a proxy for the transmission of local economic shocks—such as those arising from labor market pooling—across firms through overlapping asset networks. In areas where a cluster of similar firms taps into a common pool of skilled labor, better economic conditions in those areas can benefit all firms with a presence there (i.e., a headquarters or subsidiary). Consequently, our asset network co-investment variable may be partially capturing this indirect effect. That is, firms with asset networks tilted toward markets that are expected to outperform, may have higher levels of investment.

To examine if the strong positive asset network co-investment effect we document is more pronounced among firms that have establishments in states with considerably more expected economic activity, we follow Smajlbegovic (2019) and use the time-varying State Coincident Indexes (SCIs) developed by Crone and Clayton-Matthews (2005). SCIs describe *current* economic conditions in a state using a single statistic.[19] We couple these SCIs with State Leading indices (SLIs) produced by the Federal Reserve Bank of Philadelphia that *predict* the 6-month growth rate of each state's coincident index.[20]

Finally, we calculate the predicted growth in economic activity for each state at the beginning of each year. For each firm at the beginning of each year, we calculate a subsidiary-weighted average of expected growth in economic activity in the states to which the firm is exposed. Following Smajlbegovic (2019), we define this measure of a firm's subsidiary-weighted exposure to predicted regional economic activity as *PREA*.

$$PREA_{i,t} = \sum_{s=1}^{S} Subsid\ Share_{i,l,s,t-1} \times \frac{\Delta \widehat{SCI_{s,t+6}}}{SCI_{s,t}} \quad (11)$$

where $Subsid\ Share_{i,l,s,t}$ is the proportion of subsidiaries owned by firm i (headquartered in state l) allocated to state s in year t. $\frac{\Delta \widehat{SCI_{s,t+6}}}{SCI_{s,t}}$ is the predicted growth rate of the State Coincident Index of state s at the beginning of year t for the next 6 months. Therefore, $PREA_{i,t}$ can be interpreted as the average forecast of the local economic shocks over all firm-relevant U.S. states.

To examine the extent to which our investment commonality results (presented in Table 2) are associated with expected economic growth in the firm's subsidiary network, we again re-estimate our baseline SAR regression model of a firm's rate of investment after augmenting the specification with lagged values of *PREA*. In the results reported in column (1) of Table 5, we also report the estimated coefficient on a variable that captures the interaction between our instrumented asset network co-investment variable and *PREA* (*IV Asset Network x PREA*). The estimated coefficient on *PREA* is insignificant. The estimated coefficient on *IV Asset*

[19] To construct the state-level SCIs, Crone and Clayton-Matthews (2005) use state-level time series of nonagricultural employment, the unemployment rate, average hours worked in the manufacturing sector, as well as measures of real employment income.

[20] To estimate each SLI, the Federal Reserve Bank of Philadelphia model includes data on the past and present SCIs and other variables that lead the economy: State-level housing permits, state initial unemployment insurance claims, delivery times indicated in the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill (Smajlbegovic, 2019).

Network x PREA is positive and significant at the 10% level; that is, the effect of a firm's asset network on investment tends to be more pronounced among firms whose geographic footprint is tilted towards states with high expected growth rates as projected by the constituent labor market indicators.[21] However, the estimated coefficient on *IV Asset Network* continues to remain positive and highly significant, suggesting that labor market indicators alone are unlikely to explain the positive asset network co-investment effect. Thus, the effects of firms' asset networks on investment are not subsumed by expected economic activity in their network of subsidiary locations.

Column (2) of Table 5 displays the results obtained after replacing *IV Asset Network x PREA* with the interaction variable, *HQ Network x PREA*. The estimated coefficient on *PREA* is weakly significant. The coefficient on *HQ Network* remains insignificant, although the coefficient on *HQ Network x PREA* is positive and significant at the 5% level. This suggests that firms' headquarters networks matter only among firms whose headquarters network is tilted toward states with strong expected economic growth. However, the positive and significant coefficient on *IV Asset Network* is again unaltered by the inclusion of *HQ Network x PREA* in the specification.

Next, we replace *HQ Network x PREA* with *Industry Network* x *PREA*; these results are reported in column (3) of Table 5. The coefficient on *PREA* is insignificant. The estimated coefficient on *Industry Network* remains positive and highly significant, while the coefficient on *Industry Network x PREA* is insignificant. The strong positive relation between *IV Asset Network* and firm investment is not diminished by the inclusion of *Industry Network x PREA* in the SAR model.

For comparison to our results using state-level economic indicators, we also construct a measure of predicted national economic activity (i.e., *PNEA*) by applying equation (6) to national series rather than the state-level series. These results are reported in columns (4)-(6). Across all specifications, the estimated coefficients on *PNEA* are insignificant. Although no direct effect of *PNEA* is detected, the interactions of *PNEA* with each of our three measures of connectivity are positive and significant, which suggests an indirect role for expected national economic activity in investment decisions. Importantly, the coefficient on *IV Asset Network* remains positive and highly significant in all specifications, suggesting that while predicted national economic shocks may amplify correlated investment decisions, they do not diminish the distinct co-investment driven by overlapping asset networks.

[21] When we orthogonalize *PREA* with respect to *PNEA*, the coefficient on *IV Asset Network x PREA* becomes insignificant. This suggests that national economic shocks effectively saturate the interactive effect of local shocks on the asset network co-investment.

Taken together the results presented in Tables 4 and 5 suggest a direct (causal) link between firms' asset networks and investment, although we do find some evidence that investment is higher, all else equal, among firms that produce primarily non-tradable goods and services and among firms whose subsidiary network is tilted toward states that are expected to produce faster economic growth.

5.5 Spatial-Gravity Model

A firm's asset (subsidiary) allocation decisions are not random, and endogenous location decisions might contaminate our estimate of the asset network effect. To address this potential endogeneity, we mimic a firm's asset allocation decision using a spatial-gravity model. Specifically, we predict that a firm's allocation to a particular state is *negatively* associated with the distance between the centroids of the firm's headquarters state and the economically relevant state, and negatively related to the population in the firm's headquarters state divided by the population of the economically-relevant state. Both variables are potential attributes of a firm's neighbors. Specifically, the cost of expanding to a state is lower when 1) the distance is shorter, 2) the populations are similar (i.e., close to 1), or 3) both (Chu, Deng, and Xia, 2020).

We follow Papke and Wooldridge (1996, 2008) and estimate the predicted value of a firm's subsidiary share using a fractional logit model.

$$Subsid\ Share_{i,l,s,t} = \alpha_{i,l,s} + \beta_1 Ln\left(Distance_{l,s,t}\right) + \beta_2 Ln\left(\frac{Popl_{l,t}}{Popl_{s,t}}\right) + u_{i,l,s,t} \quad (12)$$

where $Subsid\ Share_{i,l,s,t}$ is the proportion of subsidiaries owned by firm i (headquartered in state l) allocated to state s in year t. $Distance_{l,s,t}$ is the spherical distance between the centroid of firm i's headquarters state l and subsidiary state s in year t. $\frac{Popl_{l,t}}{Popl_{s,t}}$ is the population of state l divided by the population of state s in year t. We obtain the predicted subsidiary share ($\widehat{Subsid\ Share}_{i,l,s,t}$) from estimating Equation (12) and construct a spatial weights matrix ($\widehat{W}$) and asset network co-investment ($Asset\ \widehat{Network}\ CoINV$) based on the methodology detailed in section 3.2. We then include $Asset\ \widehat{Network}\ CoINV$ as an instrumental variable in equation (10).

The first column of Table 6 presents the results of estimating our Spatial-Gravity model using a factional logit model for the sample of 268,687 firm-state pairs used in Figures 1 and 3. The results are consistent with our conjecture that firms are more likely to expand to nearby states as well as states with similar population size. More specifically, the coefficient estimates on $Ln(Distance_{l,s,t})$ and $Ln\left(\frac{Popl_{l,t}}{Popl_{s,t}}\right)$ are both negative and highly significant. As a robustness check, we also estimate our Spatial-Gravity model using a factional probit model as well as a panel regression model. These results, reported in columns (2) and (3), are very similar to those reported in column (1).

In Table 7, we reproduce the baseline results reported in Table 2 using the predicted subsidiary share obtained from estimating Equation (10) with $Asset\ \widehat{Network}\ CoINV$. This specification enables us to isolate the non-random or predictable component of the subsidiary share from its random components. The results are qualitatively similar to those reported in Table 2. This suggests that the instrumented asset network co-investment effect is unlikely to be explained by factors that may lead to endogenous colocation decisions (e.g., geographic proximity and market size). The results from estimating the first-stage regression (Equation (10)) are reported in Appendix 3. As expected, with a point estimate of 0.784 (*t*-stat: 34.60), $Asset\ \widehat{Network}\ CoINV$ is a significant predictor of the naïve *Asset Network CoINV*.

5.6 Potential Omitted Variables

We next investigate the potential impact of other omitted variables on our results. First, we create a dichotomous variable, *MNC*, that is set equal to one if the firm has operations outside of the U.S. The investment policies of multinational firms might diverge from domestic firms because of differences in cash policies, regulatory and tax regimes, and production input prices (Gu, 2017). We also expect that the co-investment of companies in the firm's headquarter network would be even less important for multinational forms. The first column of Table 8 contains results obtained from augmenting our baseline SAR regression model with *MNC*. Coefficient estimates on our control variables, other than *Tobin'sQ*, are suppressed for brevity. The estimated coefficient on *MNC* cannot be distinguished from zero. However, consistent with the baseline results reported in column (3) of Table 2, we find that industry and asset network co-investment strongly predict firm-level investment. The estimated coefficient on *HQ Network CoINV* remains insignificant.

Recent research provides evidence that investment decisions are related to a firm's valuation (Tobin's Q) as well as the valuations of peer firms (Foucault and Fresard (2014)). To examine the influence of peer valuations on investment, we construct *Asset Network Q*, which is a weighted average of peer firms' Tobin's Qs. The weights assigned to each peer firm are the same as those used to calculate the extent to which the location of a firm's subsidiaries overlap with other firms. These results are reported in column (2) of Table 8. The estimated coefficient on *Asset Network Q* is insignificant while industry and asset network co-investment continue to predict firm-level investment.

Finally, product similarity among firms may lead to correlated investment opportunities (Hoberg and Phillips, 2016). We therefore sort firms into peer groups based on Hoberg and Phillips' (2016) text-based classifications and construct *HP Industry Network CoINV,* which is a weighted average of firms in the same industry. The weights assigned to each firm pair are those used to calculate the extent to which the 10-K business descriptions of a firm overlap with the other firms. These results are reported in column (3) of Table 8. The estimated coefficient on *HP Industry Network CoINV* is positive and highly significant, suggesting that the investment decisions of same-industry firms help to explain cross-sectional variation in investment rates. Nevertheless, the estimated coefficients on *IV Asset Network CoINV* and

Industry Network CoINV remain positive and highly significant. Overall, the results reported in Table 8 suggest that the effects of co-investment by companies in a firm's asset network that we document are unlikely to be explained by these potential sources of omitted variable bias.

5.7 The Collateral Channel Mechanism

We next explore several potential channels through which the co-investment of companies in firms' asset networks could affect firm investment. The first exercise is to examine the extent to which the effects of co-investment are amplified or muted by the firm's real estate holdings. Because corporate real estate is used as collateral for debt financing, firms owning real estate in the same location(s) may be exposed to simultaneous fluctuations in the value of their real estate and thus their access to debt financing (Chaney et al., 2012). We calculate a firm's real estate ratio (*RER*) at the beginning of each year as the sum of the book value of buildings and capital leases divided by the number of employees (Tuzel, 2010; Tuzel and Zhang, 2017).[22]

In the results reported in column (1) of Table 9, *High RE* indicates that a firm's *RER* is above the median of all firms in our sample at the beginning of the year. Column (2) contains results for regressions in which *High RE* is set equal to one if a firm's *RER* is above the median of firms in the same industry. Finally, column (3) shows the results for regressions in which *High RE* is set equal to one if a firm's *RER* exceeds its own lagged *RER* (measured at the beginning of the previous year). Consistent with prior results, the estimated coefficients on *IV Asset Network* and *Industry Network co-investment* are positive and highly significant, whereas the co-investment of companies in the firm's headquarters network provides no significant explanatory power.

The primary test variable of interest, however, is the interaction of *IV Asset Network* co-investment and *High RE*. The estimated coefficient on this interaction term is positive and significant at the 5% level or higher. This indicates that high levels of real estate usage in a firm's production process amplifies the effects of co-investment by companies in the firm's asset network. This supports the existence of a collateral channel. In column (1), the estimated coefficient on asset network co-investment interacted with *High RE* is 0.16 (*t*-stat: 3.28). Said differently, *High-RE* explains about 40% of the asset network co-investment effect (0.16/(0.16+0.23)). The estimated coefficient on the interaction term is reduced somewhat in magnitude when a firm's *RER* is measured only against other firms in its industry (column (2)).

We further explore the collateral channel by examining the effects of industry, headquarters, and asset networks on debt issuance. The collateral channel is largely about how common fluctuations in real estate prices affect the desire and ability of firms to issue debt. In Table 10, we report results obtained by reproducing our baseline regression results (Table 2)

[22] Ideally, we would like to observe the market value of a firm's real estate holdings across all locations in which the firm's subsidiaries are located. However, unless there is substantial long-term differences across locations in the price appreciation rates of corporate real estate, cross-sectional variation in the book value of real estate is a reasonable proxy for the variation in market values.

using debt issuance instead of investment as the dependent variable. In column (1), we report panel regression results based on regressions of *DEBT ISS* on the lagged debt issuance of peer firms. The estimated coefficient on *HQ Network* is insignificant, which indicates that the debt issuance of companies that operate in a different industry, but that have subsidiaries in the same state(s), does not predict the debt issuance of the subject firm. In contrast, the estimated coefficient on *Industry Network* is positive and significant; that is, if peer firms are defined as those operating in the same industry, their debt issuance predicts the debt issuance of the subject firm.

To estimate the results reported in column (2), we replace the debt issuance of companies in the firm's headquarters network (*HQ Network*) with the issuance of companies in the firm's asset network and estimate our two-stage SAR model. The estimated coefficient on *IV Asset Network* is positive and significant at the 5% level. The debt issuance of firms in the same industry continues to positively predict the debt issuance of the subject firm.

The second-stage results of the SAR regression reported in column (3) contain all three proxies for a firm's peer network.[23] Consistent with the existence of a collateral channel, the debt issuance of companies in a firm's asset network positively and significantly predicts a firm's debt issuance, after controlling for headquarters and industry co-debt issuance. The coefficient estimate on *IV Asset Network Co-Debt* is 0.377 (*t*-stat: 2.11). This is very similar to the corresponding estimate on asset network co-investment reported in Table 2 (0.372, *t*-stat: 4.26). Taken together, the results displayed in Table 10 provide support for a collateral channel of debt issuance but only when a firm's peers are defined by the extent to which their asset (subsidiary) network overlaps with the subject firm. Consistent with Dougal et al. (2015), we find that comovement in debt issuance by firms headquartered in the same state does not explain correlated investment decisions.

6 Conclusion

In this paper, we investigate an investment commonality that arises from the clustering of firms' establishments in locations—asset network co-investment. We propose a theoretical framework that describes the relationships between alternative forms of co-investments. The primary predictions of this theoretical model are that co-investment implies an increase in the optimal level of firms' investments, and that the asset network co-investment effect on investment is larger than the headquarters network co-investment effect. Our empirical modelling approach links the production spillovers at the firm and the establishment levels, overcomes the reflection problem, and mitigates concerns about the endogenous location decisions of establishments. Our estimation approach integrates recent developments in both spatial econometrics and network analyses and adds to the literature on peer effects and product spillovers.

[23] The first-stage results are available in Appendix 4.

Our findings highlight the importance of asset networks in determining firm investment. The estimated coefficient on asset network co-investment is comparable to that of the industry network and increases with the extent of a firm's geographic complexity. Further analyses reveal that the asset network effect on corporate investment is stronger among firms with higher corporate real estate holdings. In addition, asset networks also shape firms' debt issuance in a material way. These findings provide evidence consistent with the collateral channel of investment. Overall, our findings have important implications for assessing the effects of the locational boundaries of firms, their overlapping locational networks, and their peer effects on firm corporate financial policy decision-making.

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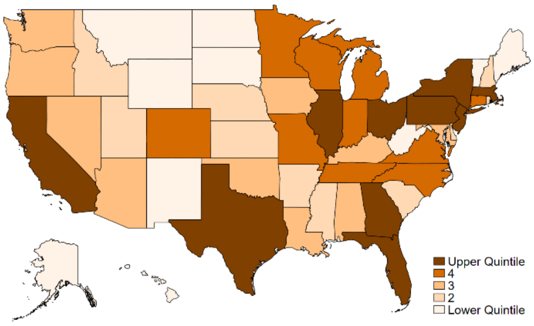
Figures and Tables

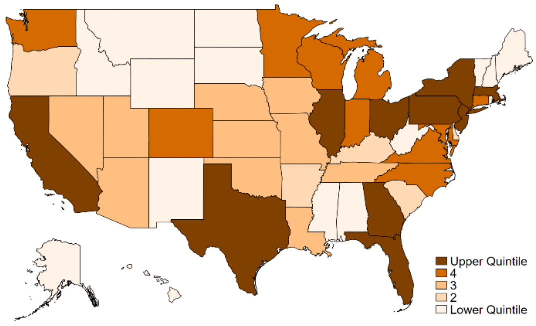
Figure 1: Geographic dispersion of firm headquarters and subsidiaries

This figure contrasts the trend in the geographic distribution of our sample firms' headquarters locations with that of their subsidiaries across the U.S. states. We calculate the percentage of firms in our sample that are headquartered in each state. We then sort the states into quintiles based on this percentage. Panels A and B depict the dispersion of firms' headquarters states in 1998 and 2019, respectively. Comparison of Panels A and B reveals that the states in which firms are headquartered have not changed much over time. Subsidiary share is the percentage of a firm's subsidiaries located in a particular state. We sort the states into quintiles based on the (simple) average of this percentage across all firms. Panels C and D show the average percentages of subsidiaries allocated to the U.S. states by a representative firm in 1998 and 2019, respectively. Comparison of Panels C and D reveals that the states in which firms have a high percentage of subsidiaries change more over time than their headquarters location.

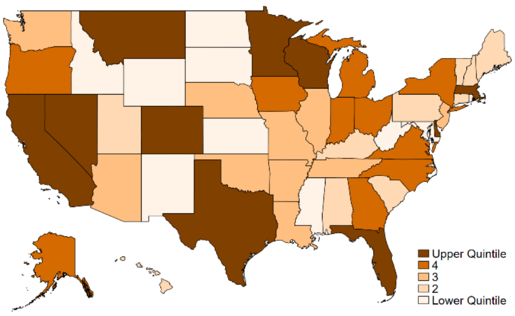
Panel A: # Headquarters (1998)



Panel B: # Headquarters (2019)



Panel C: Avg. Subsidiary Share (1998)



Panel D: Avg. Subsidiary Share (2019)

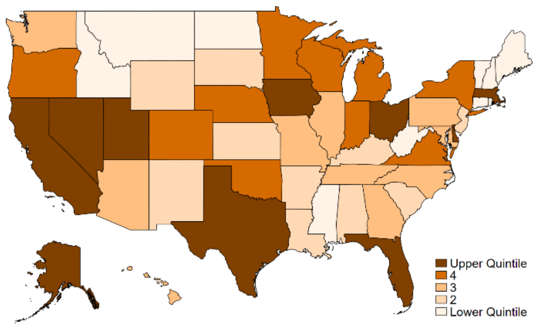
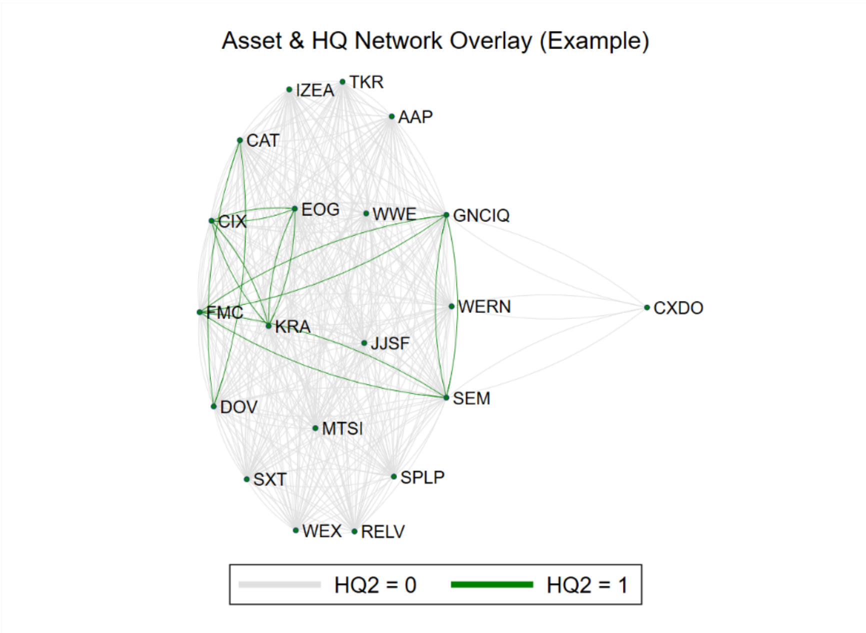


Figure 2: Comparison between headquarters and asset networks

This figure contrasts the headquarters network with the asset network based on thirty firms randomly drew from our sample. In Panel A, the green ties indicate firm pairs with the same headquarters state and the gray ones indicate firm pairs with overlapping subsidiary states. Panel B contrasts the closeness centrality statistics of asset network with that of headquarters network for all firms in 2019.

Panel A: Headquarters and asset networks overlay



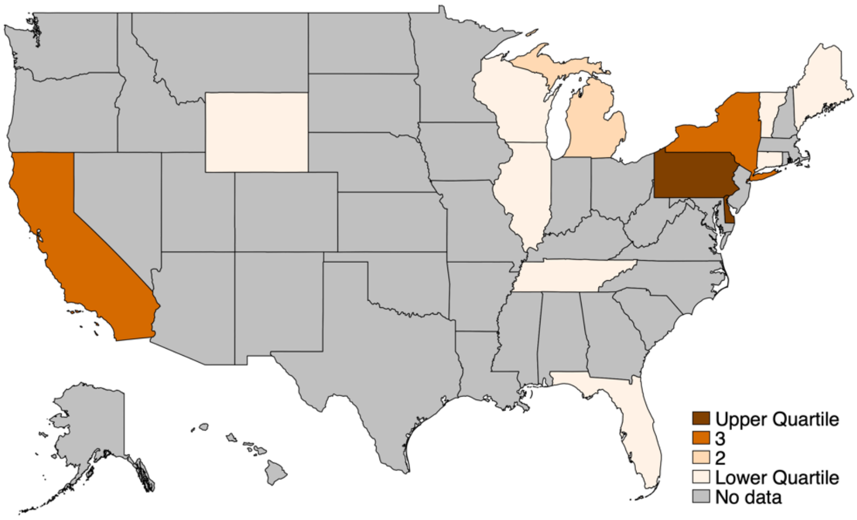
Panel B: Closeness centrality for all sample firms in 2019

Item	Closeness
Asset Network	0.88
HQ Network	0.51
Diff	0.37
t-Stat	115.75
z-Stat	41.36

Figure 3: Geographic dispersion of firm subsidiaries

This figure depicts the geographic distribution of subsidiaries across the U.S. states for two firms in our sample, Pfizer Inc. (Panel A) and Lumen Technologies Inc. (Panel B) in 2018. Pfizer is headquartered in New York and Lumen is headquartered in Louisiana.

Panel A: Pfizer Inc.



Panel B: Lumen Technologies Inc.

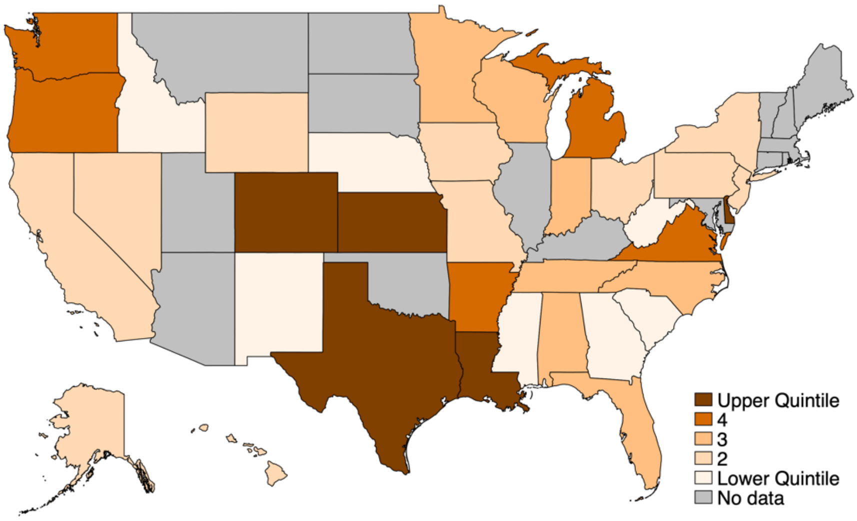


Table 1: Summary statistics

This table shows summary statistics (number of observations, mean, median, standard deviation (S.D.), and 25th and 75th percentiles) for a sample of 42,988 firm-year observations from 1998-2019. See Appendix 1 for variable descriptions.

	# Obs	Mean	Median	SD	PCT25	PCT75
Dependent variables						
INV	42,988	5.40	3.35	6.62	1.59	6.58
DEBT ISS	42,988	5.93	0.08	18.83	-0.91	7.28
Comovement variables						
CoINV						
Asset Network	42,988	5.79	5.38	1.63	4.59	6.43
HQ Network	42,988	5.91	5.06	2.69	4.11	7.14
Industry Network	42,988	5.98	5.24	3.73	3.75	6.94
Co-DEBT ISS						
Asset Network	42,988	6.15	5.41	3.49	4.42	7.39
HQ Network	42,988	7.77	5.56	9.38	2.96	9.34
Industry Network	42,988	8.30	5.41	11.63	3.42	8.86
Asset Network Q						
Tobin's	42,988	1.61	1.66	0.25	1.44	1.79
PT	40,363	1.26	1.34	0.54	0.97	1.55
Controls						
Tobin'sQ	42,988	1.61	1.17	1.43	0.82	1.86
PTQ	40,363	1.34	0.76	3.61	0.36	1.44
MNC	42,988	0.02	0.00	0.14	0.00	0.00
HP Industry Network CoINV	38,673	6.36	4.57	5.78	2.79	7.90
GEOHHI	42,988	0.58	0.52	0.29	0.35	0.85
TypeHHI	42,988	0.85	1.00	0.22	0.70	1.00
InstOwn	42,988	58.19	63.66	29.75	34.10	82.67
SIZE	42,988	6.58	6.54	2.05	5.16	7.92
Leverage	42,988	0.24	0.21	0.23	0.04	0.37
Cash Flow	42,988	0.05	0.08	0.19	0.03	0.13
RER	42,988	23.58	11.33	73.83	1.03	27.99
State-year variables						
Subsid Shr	268,687	0.191	0.065	0.268	0.023	0.227
$Distance_{i,j}$	268,687	7.090	7.193	0.827	6.483	7.747
$Popl_{i,t}/Popl_{j,t}$	268,687	0.840	0.783	1.451	-0.226	1.902

Table 2: Regression results of investment commonalities

This table shows the regression results pertaining to alternative types of commonalities in firm investment based on a sample of 42,988 firm-year observations during 1998-2019. Column (1) presents panel regression results based on the lagged aggregate investments by peer firms (*Co-INV*) as defined in Dougal, et al. (2015). Specifically, a peer firm is defined as a firm that 1) operates in the same industry as the subject firm (*Industry*) or 2) operates in a different industry but is headquartered in the same state as the subject firm (*HQ Network*). In column (2), we replace *HQ Network Co-INV* with instrumented *Asset Network CoINV* from the first-stage regressions (which are reported in Appendix 3) and estimate the Spatial Autoregressive Regression (SAR) model in Equation (8). SAR results that include all three *Co-INV* variables are presented in column (3). See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

INV	(1)	(2)	(3)
CoINV			
IV Asset Network		0.259***	0.372***
		(3.40)	(4.26)
HQ Network	0.064***		0.028
	(3.05)		(1.34)
Industry Network	0.413***	0.346***	0.399***
	(4.30)	(10.32)	(4.20)
Tobin'sQ	0.743***	0.807***	0.742***
	(6.80)	(12.07)	(6.97)
GEOHHI	0.618***	0.139	0.528***
	(3.21)	(0.90)	(2.92)
TypeHHI	0.307	0.144	0.307
	(1.01)	(0.68)	(1.03)
InstOwn	0.005	0.010***	0.005
	(1.42)	(4.49)	(1.42)
SIZE	-0.174***	-0.454***	-0.169***
	(-3.42)	(-10.20)	(-3.51)
Leverage	-1.071**	-2.335***	-1.095***
	(-2.49)	(-8.98)	(-2.64)
Cash Flow	2.946***	2.506***	2.903***
	(5.34)	(10.06)	(5.49)
Constant	1.715**	3.894***	-1.709**
	(2.48)	(4.43)	(-2.24)
1st-stage F statistics	N/A	545.38	1244.65
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.407	0.391	0.414
# Obs	42,988	42,988	42,988

Table 3: Geographic concentration and headquarters network co-investment

This table shows the Spatial Autoregressive Regression (SAR) results pertaining to the relation between firm investment and headquarters network co-investment, interacted with a dummy variable for geographically focused firms (*CONC*). Specifically, *CONC* indicates that a firm operates in less than two U.S. states including its headquarters state in Column (1), in less than three states in Column (2), and less than four states in Column (3). Control variables are the same as Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
INV	≤ 2 States	≤ 3 States	≤ 4 States
CoINV			
IV Asset Network	0.352***	0.361***	0.371***
	(3.96)	(4.11)	(4.24)
HQ Network × *CONC*	0.065**	0.039	0.003
	(1.93)	(1.28)	(0.10)
HQ Network	0.007	0.008	0.025
	(0.30)	(0.31)	(0.92)
Industry Network	0.399***	0.399***	0.398***
	(10.87)	(10.88)	(10.87)
CONC	-0.340	0.014	0.237
	(-1.48)	(0.07)	(1.19)
Tobin'sQ	0.744***	0.742***	0.742***
	(12.25)	(12.24)	(12.24)
1st-stage F statistics:	1253.25	1249.88	1247.53
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.414	0.414	0.414
# Obs	42,988	42,988	42,988

Table 4: Tradable versus Non-Tradable Industries

This table shows the Spatial Autoregressive Regression (SAR) results pertaining to the relation between firm investment and co-investments, interacted with a dummy variable for firms that produce "non-tradable" output (*Nontraded*). Specifically, *Nontraded* indicates that a firm produces goods and services that are primarily consumed in that local market instead of being exported to other distant locations. Control variables are the same as Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

INV	(1)	(2)	(3)
CoINV			
IV Asset Network	0.481***	0.488***	0.494***
	(3.87)	(3.99)	(4.01)
IV Asset Network × *Nontraded*	0.107**		
	(1.96)		
HQ Network	0.026	0.026	0.027
	(1.16)	(1.16)	(1.17)
HQ Network × *Nontraded*		0.124**	
		(2.29)	
Industry Network	0.400***	0.400***	0.400***
	(10.85)	(10.85)	(10.84)
Industry Network × *Nontraded*			0.088*
			(1.71)
Nontraded	-0.709*	-0.828**	-0.621*
	(-1.93)	(-2.22)	(-1.72)
Tobin'sQ	0.742***	0.743***	0.742***
	(12.16)	(12.16)	(12.17)
1st-stage F statistics:	271.21	298.32	298.33
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.414	0.414	0.414
# Obs	42,988	42,988	42,988

Table 5: Local and National Economic Shocks

This table shows the Spatial Autoregressive Regression (SAR) results pertaining to the relation between firm investment and co-investments interacted with the firm-level predicted regional economic activity (*PREA*) in Columns (1)-(3) and predicted national economic activity (*PNEA*) in Columns (4)-(6). Specifically, *PREA* is the weighted average of predicted regional economic activity (PREA), calculated as the predicted 6-month growth rate of each state's coincident index (SCI) normalized by SCI at the beginning of each year. SCI combines four state-level indicators (i.e., nonfarm payroll employment, average hours worked in manufacturing by production workers, unemployment rate, and the sum of wages and salaries) to summarize current economic conditions in a single statistic. *PNEA* (columns (4)-(6)) is predicted national economic activity, calculated as the predicted 6-month growth rate of the U.S. coincident index (NCI) normalized by NCI at the beginning of each year. Control variables are the same as in Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
INV	Econ = PREA			Econ = PNEA		
CoINV						
IV Asset Network	0.433***	0.423***	0.470***	0.303**	0.280**	0.391***
	(3.39)	(3.34)	(3.80)	(2.55)	(2.24)	(3.28)
IV Asset Network × Econ	0.066*			0.216***		
	(1.75)			(3.49)		
HQ Network	0.026	0.025	0.026	0.026	0.025	0.028
	(1.13)	(1.11)	(1.16)	(1.16)	(1.12)	(1.25)
HQ Network × Econ		0.091**			0.287***	
		(2.12)			(3.68)	
Industry Network	0.399***	0.399***	0.398***	0.401***	0.402***	0.400***
	(10.82)	(10.84)	(10.82)	(10.89)	(10.93)	(10.88)
Industry Network × Econ			0.044			0.144**
			(1.18)			(2.02)
Econ	-0.321	-0.503*	-0.205	0.385	0.038	0.704
	(-1.50)	(-1.95)	(-0.91)	(0.72)	(0.07)	(1.25)
Tobin'sQ	0.741***	0.741***	0.742***	0.743***	0.743***	0.743***
	(12.17)	(12.17)	(12.17)	(12.18)	(12.18)	(12.18)
1st-stage F statistics:	397.61	228.54	237.48	339.81	184.81	247.75
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.414	0.414	0.414	0.414	0.415	0.414
# Obs	42,988	42,988	42,988	42,988	42,988	42,988

Table 6: Spatial-gravity model

This table shows the results from estimating the spatial-gravity model (Equation (12)). Results from estimating a fractional logit model, a fractional probit model, and a panel regression are reported in Columns (1)-(3), respectively. $Distance_{i,j}$ is the spherical distance between the centroids of a firm's headquarters state I and a state j in which any of its subsidiary is located. $Popl_{i,t}/Popl_{j,t}$ is the population ratio between states I and j in year t. Headquarters state, subsidiary state, and year fixed effects are included. Standard errors are clustered at the subsidiary state-year level. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Subsid Share	(1) Frac. Logit	(2) Frac. Probit	(3) Panel
$Ln(Distance_{i,j})$	-0.244***	-0.137***	-0.024***
	(-29.64)	(-32.04)	(-24.88)
$ln(Popl_{i,t}/Popl_{j,t})$	-0.546***	-0.279***	-0.051***
	(-5.46)	(-4.77)	(-3.59)
HQ State F.E.s	Yes	Yes	Yes
Subsid State F.E.s	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes
R-squared	0.204	0.203	0.494
# Obs	268,687	268,687	268,687

Table 7: Regression results of investment commonalities with predicted subsidiary shares

This table shows the regression results pertaining to the relation between firm investment and asset network co-investment. Column (1) reproduces Column (1) from Table (2). In column (2), we replace HQ Network CoINV with Asset Network CoINV. We then estimate the Spatial Autoregressive Regression (SAR) model in Equation (8). We further include the predicted asset network co-investment ($Asset\ \widehat{Location}\ CoINV$) obtained from estimating Column (1) in Table 5 as an instrumental variable in the first-stage regressions. SAR results based on all three *CoINV* variables are presented in column (3). Control variables are the same as Table 2 but are suppressed for brevity. See Appendix 1 for variable descriptions and Appendix 3 for first-stage regression results. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

INV	(1)	(2)	(3)
CoINV			
IV Asset Network		0.295***	0.262***
		(3.64)	(3.09)
HQ Network	0.064***		0.038*
	(3.05)		(1.67)
Industry Network	0.413***	0.400***	0.402***
	(4.30)	(10.87)	(10.90)
Tobin'sQ	0.743***	0.743***	0.743***
	(6.80)	(12.17)	(12.19)
Constant	1.715**	-1.728***	-2.007***
	(2.48)	(-2.60)	(-3.01)
1st-stage F statistics:	N/A	880.66	835.14
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.407	0.414	0.414
# Obs	42,988	42,988	42,988

Table 8: Regression results of investment commonalities with potential omitted variables

This table presents the results based on a richer version of the Spatial Autoregressive Regression (SAR) model estimated in Column (3) in Table 2. Omitted variables of potential importance added to the baseline model include a dummy variable for multinational companies (*MNC*) in Column (1), the asset networks Tobin's Q (*Asset Q*) in Column (2), and the Hoberg-Phillips text-based industry network co-investment (*H.P. Industry*) in Column (3). Control variables are the same as Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
INV	*MNC*	*Asset Network Q*	*H.P. Industry CoINV*
CoINV			
IV Asset Network	0.372***	0.361***	0.348***
	(4.25)	(4.22)	(4.06)
HQ Network	0.028	0.029	0.003
	(1.23)	(1.24)	(0.14)
Industry Network	0.399***	0.400***	0.151***
	(10.89)	(10.95)	(3.85)
Omitted Variable	0.196	-0.436	0.261***
	(0.68)	(-1.26)	(15.92)
Tobin'sQ	0.742***	0.744***	0.719***
	(12.24)	(12.24)	(11.61)
1st-stage F statistics:	1248.04	1252.18	1083.42
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.414	0.414	0.443
# Obs	42,988	42,988	38,673

Table 9: Collateral channel of asset network co-investment

This table shows the Spatial Autoregressive Regression (SAR) results pertaining to the relation between firm investment and asset network co-investment, interacted with a dummy variable set equal to one for firms with high real estate exposure (*High RE*). Specifically, *High RE* indicates that a firm's real estate ratio is larger than the sample median (Column (1)) or the industry median (Column (2)). In the results reported in Column (3), *High RE* is equal to the increase in the firm's real estate exposure over the prior year. Control variables are the same as Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

INV	(1) Firm > All	(2) Firm > Industry	(3) RE Increase
CoINV			
IV Asset × High RE	0.164***	0.094**	0.173***
	(3.28)	(2.00)	(3.72)
IV Asset Network	0.231**	0.267***	0.455***
	(2.52)	(2.95)	(3.64)
HQ Network	0.033	0.032	0.027
	(1.37)	(1.34)	(1.21)
Industry Network	0.388***	0.373***	0.402***
	(9.63)	(9.34)	(10.95)
High RE	-0.249	0.008	-0.424
	(-0.79)	(0.03)	(-1.60)
Tobin'sQ	0.657***	0.653***	0.721***
	(11.31)	(11.38)	(11.95)
1st-stage F statistics:	179.22	178.72	182.55
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.391	0.391	0.416
# Obs	42,988	42,988	42,988

Table 10: Collateral channel and debt issuance

This table shows the regression results pertaining to alternative types of commonalities in debt issuance. Net debt issuance, *DEBT ISS*, is the dependent variable. Column (1) exhibits the panel regression results based on the use of lagged aggregate debt issuances by peer firms (*Co-DEBT ISS*) as defined in Dougal, et al. (2015), as the explanatory variable of interest. Specifically, a peer firm is a firm that 1) operates in the same industry as the subject firm (*Industry Network*) or 2) operates in a different industry but is headquartered in the same state as the subject firm (*HQ Network*). In column (2), we replace *HQ Network Co-DEBT ISS* with *Asset Network Co-DEBT ISS* and estimate the Spatial Autoregressive Regression (SAR) model in Equation (8). SAR result based on the inclusion of all three *Co-DEBT ISS* variables is presented in column (3). The first-stage results for the findings presented in columns (2) and (3) are displayed in Appendix 4. Control variables are the same as Table 2 and suppressed for brevity. See Appendix 1 for variable descriptions. Industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

DEBT ISS	(1)	(2)	(3)
Co-DEBT ISS			
IV Asset Network		0.408**	0.377**
		(2.10)	(2.11)
HQ Network	0.004		-0.001
	(0.31)		(-0.05)
Industry Network	0.024***	0.018**	0.023**
	(2.60)	(2.09)	(2.43)
Tobin'sQ	1.235***	1.424***	1.238***
	(8.51)	(8.25)	(7.63)
1st-stage F statistics:	N/A	181.90	168.24
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.086	0.086	0.086
# Obs	42,988	42,988	42,988

Appendices

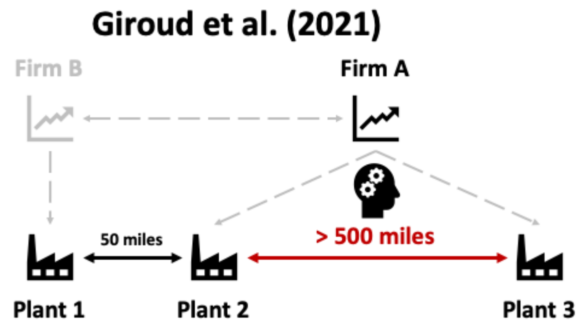
Appendix 1: Variable definition

Variable	Source	Definition
Dependent variables		
INV	Compustat	The ratio of capital expenditures (CAPX) in year *t*+1 to total assets (AT).
DEBT ISS	Compustat	The sum of the change in total long-term debt (DLTT), the change in debt due in one year (D.D.), and notes payable (N.P.), all divided by total assets.
Location variables		
Asset Location	WRDS Subsidiary Data	WRDS Subsidiary captures the states and countries in which a firm discloses material subsidiaries as required by SEC. The data are parsed from exhibits attached to a variety of filing types (e.g. 10-K, 10-Q), but primarily rely on Exhibit 21.
HQ Location	Compustat Snapshot	Compustat Snapshot discloses the state in which a firm is headquartered (STATE) in a given year.
Controls		
Tobin'sQ	Compustat	Total assets minus (CEQ) plus market equity (PRCC_C*CSHO), all divided by total assets.
PTQ	Peters and Taylor (2017)	An improved measure of Tobin's Q based on Peters and Taylor (2017). It incorporates the replacement cost of intangible capital.
H.P. Industry Network	Hoberg-Phillips Data Library	Text-based network industry classifications capture the similarity of 10-K product descriptions for each pair of firms (Hoberg and Phillips 2010, 2016).
MNC	Compustat Historical Segments	A firm is multinational if it derives sales from geographic segments other than the U.S.
GEOHHI	Compustat Historical Segments	The Herfindahl index of a firm's geographic concentration. We calculate *TypeHHI* by squaring the share of net sales (SALES) generated from each geographic segment and summing up the resulting numbers.
TypeHHI	Compustat Historical Segments	The Herfindahl index of a firm's industry concentration. We calculate *TypeHHI* by squaring the share of net sales (SALES) generated from each industry segment (Primary SIC Codes) and summing up the resulting numbers.
InstOwn	Thomson Reuters	Total institutional ownership, as a percentage of shares outstanding (instown_perc).
SIZE	Compustat	The logarithm of total assets.
Leverage	Compustat	The sum of total long-term debt and debt in current liabilities (DLC), all divided by total assets.
Cash Flow	Compustat	The sum of income before extraordinary items (I.B.) plus depreciation and amortization (D.P.) normalized by total assets.
RER	Compustat	The sum of buildings (FATB) and capitalized leases (FATL), all divided by the number of employees (EMP).
Nontraded	Delgado et al. (2016)	A dichotomous variable that equals one if a firm produces goods and services that are consumed in that local market instead of being exported to other distant locations and zero otherwise.
PSEA	The Federal Reserve Bank of Philadelphia	The weighted average of the predicted state economic activity (PSEA), calculated as the predicted 6-month growth rate of each state's coincident index (SCI) normalized by SCI at the beginning of each year. SCI combines four state-level indicators (i.e., nonfarm payroll employment, average hours worked in manufacturing by production workers, unemployment rate, and the sum of wages and salaries) to summarize current economic conditions in a single statistic.
State-year variables		
Subsid Shr	WRDS Subsidiary Data	The percentage of a firm's subsidiaries located in a particular state in a given year.
$Distance_{i,j}$	S&P Global	The sphere distance between a headquarters state *i* and subsidiary state *j*.
$Popl_{i,t}/Popl_{j,t}$	S&P Global	The ratio of state *i*'s population to state *j*'s population in year *t*.

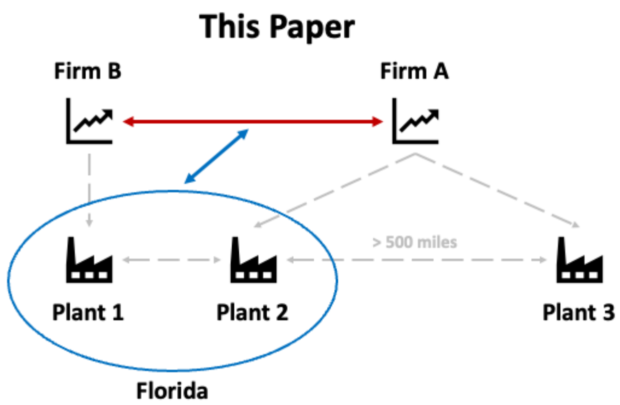
Appendix 2: Comparison between Giroud et al. (2024) and this paper

This figure highlights the distinctions between Giroud et al. (2024) (Panel A) and this paper (Panel B). Specifically, an investment by firm A might affect firm B's investment through overlapping exposure to a particular location (e.g., Florida). One way to think about this overlapping structure is from a "common ownership" perspective (e.g., firms A and B 'commonly own' a few locations). In Panel B, the common ownership of plants has real effects on firms' rate of investment ("blue" double-sided arrow line) and helps link prior studies looking at inter-firm networks ("red" double-sided arrow line) to cross-plant spillovers. The "blue" curve also suggests signs of reverse causation from the inter-firm network to the asset network. We address this issue using a spatial-gravity model.

Panel A



Panel B



Appendix 3: First-stage regression results for Tables 2 and 7

This table shows the first-stage regression results for the SAR results reported in Tables 2 and 7. Columns (1) and (2) correspond to Columns (2) and (3) in Table 2, respectively. Columns (3) and (4) correspond to Columns (2) and (3) in Table 7, respectively. *Asset…* are the spatially lagged variables. See Appendix 1 for variable descriptions. Baseline variables and industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Asset Network CoINV	(1)	(2)	(3)	(4)
$Asset\ \widehat{Network}\ CoINV$			0.787***	0.784***
			(34.54)	(34.60)
Asset Q	0.275***	0.297***	0.160***	0.161***
	(3.40)	(4.43)	(2.96)	(2.96)
Asset GEOHHI	-0.399**	0.073	-1.281***	-1.274***
	(-2.41)	(0.48)	(-11.49)	(-11.41)
Asset TypeHHI	3.57***	1.711**	1.918***	1.909***
	(3.56)	(2.58)	(3.79)	(3.77)
Asset InstOwn	0.027***	0.012**	0.011**	0.011**
	(3.54)	(2.09)	(1.94)	(1.91)
Asset SIZE	-0.760***	-0.491***	-0.430***	-0.428***
	(-7.00)	(-6.66)	(-5.81)	(-5.78)
Asset Leverage	3.904***	3.177***	1.656***	1.666***
	(6.22)	(6.04)	(3.37)	(3.38)
Asset Cash Flow	4.894***	3.926***	1.771***	1.778***
	(8.87)	(8.92)	(4.13)	(4.13)
1st-stage F statistics:	545.38	1244.65	880.66	835.14
Baseline variables	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
# Obs	42,988	42,988	42,988	42,988

Appendix 4: First-stage regression results for Table 10

This table shows the first-stage regression results for the SAR results reported in Table 10. Columns (1) and (2) correspond to Columns (2) and (3) in Table 10, respectively. *Asset…* are the spatially lagged variables. See Appendix 1 for variable descriptions. Baseline variables and industry (4-digit SIC) and year fixed effects are included. Standard errors are clustered at the industry-year level. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Asset Network Co-DEBT ISS	(1)	(2)
Asset Q	0.107	0.107
	(0.74)	(0.74)
Asset GEOHHI	-1.595**	-1.594**
	(-4.96)	(-4.96)
Asset TypeHHI	9.105***	9.107***
	(5.62)	(5.62)
Asset InstOwn	0.015	0.015
	(1.33)	(1.32)
Asset SIZE	-0.528***	-0.526***
	(-3.25)	(-3.24)
Asset Leverage	25.642***	25.638***
	(21.33)	(21.34)
Asset Cash Flow	-4.706***	-4.708***
	(-4.16)	(-4.16)
1st-stage F statistics:	181.90	168.24
Baseline variables	Yes	Yes
Industry F.E.	Yes	Yes
Year F.E.	Yes	Yes
# Obs	42,988	42,988

Appendix 5: Constructing asset network co-investment

A hypothetical firm example:

Firm\Subsid Shr\State	INV	CA	FL	AK	Sum
Firm 1	3	0.6	0.3	0.1	1
Firm 2	5	0	1	0	1
Firm 3	8	1	0	0	1

Our first step is to pair up firm-state observations and determine the percentage of overlapping subsidiary shares.

Firm *i*	State	Subsid Shr *i*	Firm *j*	Subsid Shr *j*	Same State	% Same State
Firm 1	CA	0.6	Firm 2	0	0	0
Firm 1	FL	0.3	Firm 2	1	1	0.3
Firm 1	AK	0.1	Firm 2	0	0	0
Firm 1	CA	0.6	Firm 3	1	1	0.6
Firm 1	FL	0.3	Firm 3	0	0	0
Firm 1	AK	0.1	Firm 3	0	0	0
Firm 2	CA	0	Firm 1	0.6	0	0
Firm 2	FL	1	Firm 1	0.3	1	1
Firm 2	AK	0	Firm 1	0.1	0	0
Firm 2	CA	0	Firm 3	1	0	0
Firm 2	FL	1	Firm 3	0	0	0
Firm 2	AK	0	Firm 3	0	0	0
Firm 3	CA	1	Firm 1	0.6	1	1
Firm 3	FL	0	Firm 1	0.3	0	0
Firm 3	AK	0	Firm 1	0.1	0	0
Firm 3	CA	1	Firm 2	0	0	0
Firm 3	FL	0	Firm 2	1	0	0
Firm 3	AK	0	Firm 2	0	0	0

Next, we sum up % Same State across all states for firm *i*-firm *j* pairs and determine the minimum of the aggregate statistics (e.g. firm 1-firm 2 and firm 2-firm 1).

Firm *i*	Firm *j*	Total % Same State	Min
Firm 1	Firm 2	0.3	0.3
Firm 1	Firm 3	0.6	0.6
Firm 2	Firm 1	1	0.3
Firm 2	Firm 3	0	0
Firm 3	Firm 1	1	0.6
Firm 3	Firm 2	0	0

We then estimate the asset network weights matrix using the minimum values

	Firm 1	Firm 2	Firm 3	Row Sum
Firm 1	0	0.3	0.6	0.9
Firm 2	0.3	0	0	0.3
Firm 3	0.6	0	0	0.6

The last step is row-normalization:

	Firm 1	Firm 2	Firm 3	New Row Sum
Firm 1	0	0.33	0.67	1
Firm 2	1	0	0	1
Firm 3	1	0	0	1

Now we proceed to estimate *Asset* Network *CoINV*. Here are the investment values from our hypothetical firm example:

	INV
Firm 1	3
Firm 2	5
Firm 3	8

Given the row-normalized weights matrix and the investment values, Asset Network CoINV would be:

	Asset Network CoINV
Firm 1	7
Firm 2	3
Firm 3	3

Appendix 6: Technical Appendix

This Appendix provides explanations of how we derive various modelling results.

The first order conditions on equation (4) imply:

$$C_N = w - \gamma F_N = 0 \qquad (A6.1)$$
$$C_{INV} = P_{INV} - \lambda\psi_{INV} - \gamma F_{INV} = 0 \qquad (A6.2)$$
$$\lambda[\dot{K} - \psi(\alpha, INV, \overline{INV})] = 0 \qquad (A6.3)$$
$$\gamma[Y - F(A_Y, INV, \overline{INV}, N)] = 0 \qquad (A6.4)$$

Hayashi's (1982) formulation of $Tobin's\ Q$ (denoted as Q), along with our (A6.1), (A6.2), (A6.3), (A6.4), imply:

$$INV^* = h(Q, A_C, \alpha, X;\ P_{INV}, w, Y, K, \gamma, A_Y, \delta) \qquad (A6.5)$$

Equation $(A6.5)$ can be derived as follows. First, Hayashi (1982) notes that *Tobin's Q* can be written as:

$$Q \equiv \frac{\lambda}{P_{INV}} \qquad (A6.6),$$

where λ is the "shadow price" of additional INV (analogous to Hayashi, 1982), based on the first order conditions of the firm's optimization problem.

Based on equation (A6.2) above, equation $(A6.6)$ implies:

$$Q = \frac{[1 - [\gamma\, F_{INV}/P_{INV}]]}{\psi_{INV}} \qquad (A6.7)$$

Equation $(A4.1)$ implies that $\gamma = w/F_N$ and therefore:

$$Q\psi_{INV} = 1 - \left[{}^{wF_{INV}}/_{P_{INV}F_N}\right] \qquad (A6.8)$$

Also, $(A6.3)$ and $(A6.6)$ imply that $QP_{INV}\left[\dot{K} - \psi\right] = 0 \qquad (A6.9)$

The following function, Φ, implicitly defines INV^*:

$$\Phi = Q\psi_{INV} - \left[1 - \left[{}^{wF_{INV}}/_{P_{INV}F_N}\right]\right] + QP_{INV}\left[\dot{K} - \psi\right] + \frac{w}{F_N}[Y - F] = 0 \qquad (A6.10)$$

${}^{\partial INV^*}/_{\partial A_{HQ}}$ and ${}^{\partial INV^*}/_{\partial A_A}$ are given as follows (from the Implicit Function Theorem):

$$\partial INV^* / \partial A_{HQ} = {-\Phi_{A_{HQ}}} / {\Phi_{INV}} \qquad (A6.11)$$

$$\partial INV^* / \partial A_A = {-\Phi_{A_A}} / {\Phi_{INV}} \qquad (A6.12)$$

Proof of Propositions 1 and 2:

Given the strict concavity of F, Assumption 2, and Assumption 5, it can be shown that:

$\Phi_{INV} < 0$ $(A6.10')$.

Next, $-\Phi_{A_A} = \frac{-w}{F_N}\left[\frac{F_{INV,A_A}}{P_{INV}} - \frac{F_{INV}F_{N,A_A}}{P_{INV}F_N} - \frac{YF_{N,A_A}}{F_N} - F_{A_A} - \frac{FF_{N,A_A}}{wF_N}\right]$ $\qquad (A6.13)$

Sufficient conditions for $-\Phi_{A_A} < 0$ to hold are that labor is sufficiently productive (i.e., F_N is large, as given by Assumption 1); A_A has a positive effect on F_{INV} (given by Assumption 3); and A_A has a positive effect on F_N (given by Assumption 4). Assumption 5 implies that F_{N,A_A} is small relative to F_{INV,A_A}. Therefore, assuming F_{A_A} is small, then $-\Phi_{A_A} < 0$, which together with $(A6.10')$ and $(A6.12)$, implies that $\partial INV^* / \partial A_A > 0$.

Analogous lines of reasoning imply that $-\Phi_{A_{HQ}} < 0$ and therefore $\partial INV^* / \partial A_A = {-\Phi_{A_{HQ}}} / {\Phi_{INV}} > 0$.

Proof of Proposition 3:

Given that Propositions 1 and 2 hold, the following are sufficient conditions for ${-\Phi_{A_A}} / {\Phi_{INV}} > {-\Phi_{A_{HQ}}} / {\Phi_{INV}}$:

1. F_{INV,A_A} is sufficiently large relative to $F_{INV,A_{HQ}}$
2. F_{N,A_A} is sufficiently large relative to $F_{N,A_{HQ}}$
3. F_{A_A} is sufficiently small relative to $F_{A_{HQ}}$

Based on the assumptions stated in Proposition 3, together with $(A6.10')$, this proposition holds.

Proof of Proposition 4:

Based on $(A6.10)$, the Implicit Function Theorem implies that:

$$\partial INV^* / \partial \alpha = {-\Phi_\alpha} / {\Phi_{INV}} \qquad (A6.14)$$

Therefore,

$$-\Phi_\alpha = -Q\left[\psi_{INV,\alpha} - P_{INV}\psi_\alpha\right] \qquad (A6.15)$$

Based on Assumption 7 and assuming ψ_α is sufficiently large in absolute value and $\psi_{INV,\alpha}$ is sufficiently small in absolute value, then $-\Phi_\alpha < 0,$ and together with $(A6.10')$, therefore ${\partial INV^*}/{\partial\alpha} > 0$.

Proof of Proposition 5:

From the Implicit Function Theorem,

$$ {\partial INV^*}/{\partial Q} = {-\Phi_Q}/{\Phi_{INV}} \qquad (A6.16) $$

Also, $-\Phi_Q = -\left[\psi_{INV} + P_{INV}\,[\dot{K} - \psi]\right]$ $\qquad (A6.17)$

Assumption 8, together with $(A6.3)$ and $(A6.17)$, imply $-\Phi_Q = -\psi_{INV}$, which, due to Assumption 6, implies that $-\Phi_Q < 0$. In turn, $(A6.16)$ and $(A6.10')$ imply that ${\partial INV^*}/{\partial Q} > 0$.