RIETI Discussion Paper Series 24-E-029

Empirical Estimation of the Propagation of Investment Spikes over the Production Network

NIREI, Makoto
RIETI

RIETI
Research Institute of Economy, Trade & Industry, IAA
The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 24-E-029
February 2024

Empirical Estimation of the Propagation of Investment Spikes over the Production Network*

Makoto Nirei
University of Tokyo and RIETI

Abstract
This study estimates the degree of complementarity between firm investment spikes linked by production networks. A customer firm's increase in capital by more than 20% (an investment spike) raises its future demand for intermediate inputs, increasing the likelihood of the supplier's spike. Similarly, a supplier's investment spike lowers the future cost of intermediate goods demanded by its customer and induces the customer's investment spike. We use firm-level panel data from the Japanese business survey and transaction network data to estimate this complementarity in investment decisions. The estimates show that one firm's investment spike induces, on average, 0.088 firms to conduct investment spikes, indicating that an investment spike shock can propagate through the production network to upstream and downstream firms.

Keywords: investment spike; lumpy investment; complementarity; production network; supply chain
JEL classification: L16 and E22

*This study results from a joint project of the "Innovation, Knowledge Creation and Macroeconomy" project undertaken at the Research Institute of Economy, Trade and Industry (RIETI) and the CREPE-TSR research project of TOKYO SHOKO RESEARCH, LTD. and the Center for Research and Education in Program Evaluation at the University of Tokyo. This study uses data collected by the Ministry of Economy, Trade and Industry for the Basic Survey of Japanese Business Structure and Activities. I would like to thank the participants of the RIETI DP Seminar for their helpful comments.

1 Introduction

Firms' investments have been noted to exhibit lumpy behavior (Doms and Dunne (1998); (Cooper et al., 1999)). There is wide dispersion in the investment–capital ratio, and episodes exceeding 20% are common. These investment spikes are considered an extensive margin adjustment of capital, such as new establishments, factories, large equipment, or research centers.

Investment spikes also tend to coincide. Cooper and Haltiwanger (1996) and Gourio and Kashyap (2007) document that much of the variation in aggregate investments is attributed to concurrent investment spikes across firms and industries, which can occur due to common exogenous shocks and endogenous complementary decisions in firms' investments. There have been efforts to empirically estimate complementarity across firms' investment decisions (Cooper and Haltiwanger (1996); Guiso et al. (2017)). However, it has been difficult to isolate the effect of the strategic complementarity from common shocks.

Recently, the availability of firm-level network data has opened up the possibility of empirically isolating the propagation effects running through production network links. Carvalho et al. (2021) used firm network data to identify the propagation effects of a shock emanating from a natural disaster.

In this paper, we estimate the propagation effect of a firm's investment spike on its transaction partner firms. We first present a model of a firm's lumpy investments when it is a monopolistic supplier of a differentiated good, which is used as a final and intermediate good. The firm also uses a set of differentiated intermediate inputs. The model assumes that each firm's set of customer and supplier firms is given and fixed over time. We then define a general equilibrium in which wages and returns to capital are determined in equilibrium. In a stationary equilibrium, where wages and capital returns are constant over time, we present an optimal lumpy investment function that maps the firm's productivity and customers' and suppliers' lumpy investments to the firm's investment decision. This provides us with an equation to structurally estimate the complementarity of investment spikes.

We combine the transaction network data with the firm-level panel data compiled from a Japanese business survey to estimate the complementarity. We compute the fraction of customer or supplier firms engaging in lumpy investments and their profitability measures. Considering the firm and year fixed effects, the logit regression shows there is a significant effect of a firm's investment spike on the fraction of partner firms with lumpy investments. The result is robust when the estimation is switched to a linear probability model.

The remainder of this paper proceeds as follows. Section 2 presents the model and the equation for structural estimation. Section 3 explains the data. Section 4 shows the estimation results. Section 5 explores the aggregate implications of the estimates. Section 6 concludes.

2 Model

2.1 Firms

A model economy has a unitary measure of firms indexed by $i \in [0, 1]$, each producing a differentiated product. Consider that firm i uses intermediate goods produced by suppliers and sells its products to customers and a final goods producer. The supply chain network is denoted by an adjacency matrix S, where its nonzero element $S_{ij} = 1$ indicates that firm i uses good j as an intermediate input. The set of i's suppliers is denoted by $I_i := \{j : S_{ij} = 1\}$, and the set of i's customer is denoted by $O_i := \{j : S_{ji} = 1\}$. We assume both I_i and O_i are finite for all i.

The intermediate goods are aggregated to form an intermediate composite good as

$$m_{i,t} = \left(\sum_{j \in I_i} x_{ij,t}^{(\phi-1)/\phi} |I_i|^{-1/\phi} \right)^{\phi/(\phi-1)}$$

where cardinality $|I_i|$ indicates the number of i's suppliers.

The final good is competitively produced using the following production function.

$$Y_t = \left(\int_0^1 \chi_j x_{Yj,t}^{(\phi-1)/\phi} dj \right)^{\phi/(\phi-1)}$$

The final goods are used for consumption and investment.

Given prices $(p_{j,t})_j$, firms' cost-minimization leads to demand functions for good j as

$$x_{ij,t} = \left(\frac{p_{j,t}}{P_{i,t}} \right)^{-\phi} \frac{m_{i,t}}{|I_i|}, \tag{1}$$

$$x_{Yj,t} = p_{j,t}^{-\phi} \chi_j Y_t, \tag{2}$$

where $P_{i,t} := \left(\sum_{j \in I_i} p_{j,t}^{1-\phi} / |I_i| \right)^{1/(1-\phi)}$. The unit cost of the final good, $\left(\int_0^1 \chi_j p_{j,t}^{1-\phi} dj \right)^{1/(1-\phi)}$, is set to 1. Firm i faces demand from the final good producers and firm i's customers. The total demand for i is written as a function of $p_{i,t}$ as

$$x_{Yi,t} + \sum_{j \in O_i} x_{ji,t} = p_{i,t}^{-\phi} D_{i,t}, \tag{3}$$

$$D_{i,t} := \chi_i Y_t + \sum_{j \in O_i} \frac{P_{j,t}^{\phi} m_{j,t}}{|I_j|}. \tag{4}$$

Firm i uses the composite intermediate good $m_{i,t}$, labor $l_{i,t}$, and capital $k_{i,t}$ to monopolistically supply good i using a production function specified as

$$y_{i,t} = A_{i,t} m_{i,t}^{\alpha} l_{i,t}^{\beta} k_{i,t}^{\gamma} \tag{5}$$

with returns to scale $\alpha + \beta + \gamma \leq 1$. $A_{i,t}$ denotes firm-specific total factor productivity.

We assume that capital investment is indivisible up to "lumpiness" parameter λ_i. Hence, a firm's choice for capital is restricted to a discrete set:

$$k_{i,t+1} \in \{\lambda_i^n (1 - \delta_i) k_{i,t}\}_{n=0,\pm 1,\pm 2,\dots}.$$

We assume $\lambda_i > 1/(1 - \delta_i)$ for all i.

Firm i's static profit maximization problem given k_i is

$$\pi_{i,t}(k_{i,t}) = \max_{p_{i,t}, y_{i,t}, m_{i,t}, l_{i,t}} p_{i,t} y_{i,t} - P_{i,t} m_{i,t} - W_t l_{i,t}$$

subject to production function (5) and demand function $y_{i,t} = p_{i,t}^{-\phi} D_{i,t}$. Solving the cost-minimization problem, the profit function is derived as follows:

$$\pi_{i,t}(k_{i,t}) = \omega_t \left(\left(\frac{A_{i,t}}{P_{i,t}^{\alpha}} \right)^{1-1/\phi} D_{i,t}^{1/\phi} \right)^{\frac{1}{1-(\alpha+\beta)(1-1/\phi)}} k_{i,t}^{\theta},$$

$$\theta := \frac{\gamma(1 - 1/\phi)}{1 - (\alpha + \beta)(1 - 1/\phi)},$$

$$\omega_t := \left(1 - (\alpha + \beta) \left(1 - \frac{1}{\phi} \right) \right) \left(\left(1 - \frac{1}{\phi} \right)^{\alpha+\beta} \frac{\alpha^{\alpha} \beta^{\beta}}{W_t^{\beta}} \right)^{\frac{1-1/\phi}{1-(\alpha+\beta)(1-1/\phi)}}.$$

Future productivities $A_{i,t+1}$ may incur idiosyncratic shocks; however, we assume that their realizations, and relevant prices, $P_{i,t+1}$, W_{t+1}, and R_{t+1}, are known in t. Firm i maximizes its sum of future discounted profits, $\sum_{\tau=t}^{\infty}(\Pi_{s=t+1}^{\tau}R_s^{-1})\pi(k_{i,\tau})$, where R_t^{-1} denotes the discount factor. The firm value relevant to choice of $k_{i,t+1}$ is

$$R_{t+1}^{-1}(\pi_{i,t+1}(k_{i,t+1}) + (1-\delta_i)k_{i,t+1}) - k_{i,t+1}.$$

We recall that $k_{i,t+1}$ must be chosen from $\{(1-\delta_i)k_{i,t}\lambda_i^n\}_{n=0,\pm1,\pm2,\ldots}$. Then, there must be a lower threshold above which i chooses not to increase capital from $(1-\delta_i)k_{i,t}$. At the optimal threshold, the firm is indifferent to investing. Thus, the optimal threshold $k_{i,t}^*$ satisfies the following equation:

$$R_{t+1}^{-1}(\pi_{i,t+1}(k_{i,t}^*)+(1-\delta_i)k_{i,t}^*)-k_{i,t}^* = R_{t+1}^{-1}(\pi_{i,t+1}(\lambda_i k_{i,t}^*)+(1-\delta_i)\lambda_i k_{i,t}^*)-\lambda_i k_{i,t}^*.$$

Solving for $k_{i,t}^*$, we obtain

$$k_{i,t}^* = \left(\left(\frac{\lambda_i^\theta - 1}{\lambda_i - 1}\frac{\omega_{t+1}}{R_{t+1}-1+\delta_i}\right)^{1-(\alpha+\beta)\left(1-\frac{1}{\phi}\right)}\left(\frac{A_{i,t+1}}{P_{i,t+1}^\alpha}\right)^{1-\frac{1}{\phi}} D_{i,t+1}^{1/\phi}\right)^{\frac{1}{1-(\alpha+\beta+\gamma)\left(1-\frac{1}{\phi}\right)}}. \quad (6)$$

This determines the optimal threshold policy by which firm i chooses to invest in t only if $k_{i,t} < k_{i,t}^*$. On the right-hand side, $D_{i,t+1}$ summarizes the effect of i's customers and $P_{i,t+1}$ the effect of i's suppliers, as discussed below. Under the constant returns to scale $\alpha+\beta+\gamma=1$, the optimal threshold $k_{i,t}^*$ in (6) is a linear function of $D_{i,t+1}$.

From (6), we can see that firm i's lumpy investment is a strategic complement to the investment decision of firm i's customers and suppliers. We first investigate the effect of i's customers. Suppose customer j of firm i decides to invest in t. Then, $k_{j,t+1}$ increases to $\lambda_j(1-\delta_j)k_{j,t}$, and output $y_{j,t+1}$ also increases. This raises the demand for intermediate inputs $m_{j,t+1}$, affecting the total demand for i through $P^{\phi}_{j,t+1}m_{j,t+1}/|I_j|$, as in (4). Thus, a lumpy investment by j raises the investment threshold of i provided that $P_{j,t+1}$ is fixed, i.e., j's supplier prices are unaffected. An increase in $k^*_{i,t}$ causes a lumpy investment of i in t if $k_{i,t-1}$ is close to the threshold $k^*_{i,t}$. In this way, the likelihood of i's lumpy investment is increased by the lumpy investments of i's customers.

Suppliers also affect the threshold. We note that (6) includes $P_{i,t+1}$, which is the unit cost of i's intermediate inputs. When i's supplier j invests in t and increases the level of capital in $t+1$, it increases optimal output $y_{j,t+1}$ and decreases optimal price $p_{j,t+1}$. Since $p_{j,t+1}$ is a part of i's intermediate unit cost, a decrease of $p_{j,t+1}$ decreases $P_{i,t+1}$, leading to an increase in $k^*_{i,t}$. Namely, j's capital investment decreases j's future price, reducing i's future intermediate cost and inducing i to produce more in the future, calling for investment today.

2.2 Investment spike probability in a stationary equilibrium

We consider a stationary equilibrium in which the real wage rate and discount factor are constant at W and R, respectively. For simplicity, we assume that $A_{i,t}$ is constant at A for all i and t. The aggregate investment is defined as $X_t = \int_{i:k^*_{i,t}>(1-\delta_i)k_{i,t}}(\lambda_i-(1-\delta_i))k_{i,t}di$.

To close the model, we assume representative households that supply labor L_t and consume C_t. Households maximize utility $\sum_{t=0}^{\infty} \beta^t U(C_t, L_t)$ subject to budget constraints,

$$\int_0^1 q_{i,t} s_{i,t+1} di + C_t = W L_t + \int_0^1 (q_{i,t} + \pi_{i,t} - k_{i,t+1} + (1-\delta) k_{i,t}) s_{i,t} di,$$

where $s_{i,t}$ denotes the stock share of firm i and $q_{i,t}$ denotes its price in t. The supply of the share is normalized to 1. The market clearing condition for final goods is $Y_t = C_t + X_t$. At a stationary equilibrium, $R = 1/\beta$, $-U_L/U_C = W$, and $Y = C + X$ must hold.

We define the gap between the current capital and the threshold level capital as the logarithmic difference between $k_{i,t}$ and $k^*_{i,t}$, normalized by the lumpiness,

$$s_{i,t} := \frac{\log k_{i,t} - \log k^*_{i,t}}{\log \lambda_i}.$$

The lower threshold of a lumpy investment in the stationary equilibrium is determined by

$$k^*_{i,t} = \left(\left(\frac{\lambda_i^\theta - 1}{\lambda_i - 1} \frac{\omega}{R - 1 + \delta_i} \right)^{1-(\alpha+\beta)\left(1-\frac{1}{\phi}\right)} \left(\frac{A_{i,t+1}}{P^\alpha_{i,t+1}} \right)^{1-\frac{1}{\phi}} D^{1/\phi}_{i,t+1} \right)^{\frac{1}{1-(\alpha+\beta+\gamma)\left(1-\frac{1}{\phi}\right)}}$$

where (ω, R) is the stationary value of (ω_t, R_t).

In the stationary equilibrium, firm i's state $s_{i,t}$ follows an optimal (S,s) rule in which $s_{i,t}$ evolves according to

$$s_{i,t} = s_{i,t-1} + \frac{\log(1-\delta_i)}{\log \lambda_i} - \frac{\left(1 - \frac{1}{\phi}\right) \log \left(\frac{A_{i,t+1}}{A_{i,t}} \left(\frac{P_{i,t}}{P_{i,t+1}} \right)^\alpha \right) + \frac{1}{\phi} \log \frac{D_{i,t+1}}{D_{i,t}}}{(1 - (\alpha+\beta+\gamma)(1-1/\phi)) \log \lambda_i}, \quad (7)$$

if $s_{i,t} \geq 0$, and $s_{i,t}$ is reset to 1 if the right-hand side of the above equation is less than 0.

An invariant distribution of state $s_{i,t}$ is uniform. This can be seen as follows. Consider a type of firm with (λ_i, δ_i). State $s_{i,t}$ evolves as firms' idiosyncratic shocks drive $(A_{i,t}, P_{i,t}, D_{i,t})$. If the initial distribution $s_{i,0}$ is uniform over a circle with unit circumference, any realization of $(A_{i,t}, P_{i,t}, D_{i,t})$ rotates the distribution over the circle. Hence, the unit uniform distribution is time-invariant for each type. Because the mixture of uniform distribution is also uniform, even when the economy has different types of firms in terms of their lumpiness and depreciation rate, the unit uniform distribution of $s_{i,t}$ is time-invariant. Under mild conditions, the evolution of $s_{i,t}$ is also stationary (Caballero and Engel (1991); Nirei (2015)).

We focus on a stationary equilibrium in which $s_{i,t}$ follows the stationary uniform distribution over $(0, 1]$. Let $d_{i,t}$ be an indicator function that takes 1 when i experiences an investment spike in period t and 0 otherwise. Then, the unconditional probability of firm i's spike investment is derived as a linear function:

$$\begin{aligned}\Pr(d_{i,t} = 1) =& \frac{1}{(1-(\alpha+\beta+\gamma)(1-1/\phi))\log\lambda_i} \\ & \times\left[\left(1-\frac{1}{\phi}\right)\left(\overbrace{(\log A_{i,t+1}-\log A_{i,t})}^{\text{Productivity shock}} - \alpha\overbrace{(\log P_{i,t+1}-\log P_{i,t})}^{\text{Supplier shock}}\right)\right. \\ & \left. + \frac{1}{\phi}\overbrace{(\log D_{i,t+1}-\log D_{i,t})}^{\text{Customer shock}}\right]. \qquad (8)\end{aligned}$$

An innovation of $D_{i,t}$ represents a shock from i's customer firms, as their intermediate demand induces i's lumpy investment. An innovation of $P_{i,t}$ represents a shock from i's suppliers. A supplier's lumpy investment reduces i's intermediate cost and induces i's investment. Finally, an innovation of

$A_{i,t}$ denotes i's productivity shock.

2.3 Propagation of investment spikes over the supply chain

The customer and supplier shocks in Equation (8) arise from their lumpy investments. First, we investigate the customer shock. The optimal supply function of a customer j is

$$y_{j,t} = \tilde{\omega}_t \left(A_{j,t} P_{j,t}^{\alpha} D_{j,t}^{\frac{\alpha+\beta}{\phi}} k_{j,t}^{\gamma} \right)^{\frac{1}{1-(\alpha+\beta)(1-1/\phi)}},$$

$$\tilde{\omega}_t := \left(\left(1 - \frac{1}{\phi}\right)^{\alpha+\beta} \frac{\alpha^{\alpha}\beta^{\beta}}{W_t^{\beta}} \right)^{\frac{1}{1-(\alpha+\beta)(1-1/\phi)}}.$$

Using the derived demand for intermediate goods, we obtain

$$\begin{aligned}
&P_{j,t}^{\phi} m_{j,t} = \alpha \left(1 - 1/\phi\right) P_{j,t}^{\phi-1} D_{j,t}^{1/\phi} y_{j,t}^{1-1/\phi} \\
&= \alpha \left(1 - 1/\phi\right) P_{j,t}^{\phi-1} D_{j,t}^{1/\phi} \tilde{\omega}_t^{1-1/\phi} \left(A_{j,t} P_{j,t}^{\alpha} D_{j,t}^{\frac{\alpha+\beta}{\phi}} k_{j,t}^{\gamma} \right)^{\frac{1-1/\phi}{1-(\alpha+\beta)(1-1/\phi)}} \\
&= \alpha \left(1 - \frac{1}{\phi}\right) \tilde{\omega}_t^{1-\frac{1}{\phi}} \left(P_{j,t}^{\left(1-\frac{1}{\phi}\right)\left((\phi+\alpha)-(\alpha+\beta)\phi\left(1-\frac{1}{\phi}\right)\right)} D_{j,t}^{\frac{1}{\phi}} \left(A_{j,t} k_{j,t}^{\gamma}\right)^{1-\frac{1}{\phi}} \right)^{\frac{1}{1-(\alpha+\beta)\left(1-\frac{1}{\phi}\right)}}.
\end{aligned}$$

Suppose that j is a customer of firm i: $j \in O_i$. Then, j's lumpy investment's impact on i's lumpy investment is

$$\begin{aligned}
&\Pr(d_{i,t} = 1 \mid d_{j,t} = 1) - \Pr(d_{i,t} = 1 \mid d_{j,t} = 0) \\
&= \frac{\log D_{i,t+1} - \log D_{i,t}}{(\phi + (\alpha + \beta + \gamma)(1 - \phi)) \log \lambda_i} \\
&= \frac{\lambda_j^{\frac{\gamma(1-1/\phi)}{1-(\alpha+\beta)(1-1/\phi)}} - 1}{(\phi + (\alpha + \beta + \gamma)(1 - \phi)) \log \lambda_i} \frac{P_{j,t}^{\phi} m_{j,t}}{|I_j| D_{i,t}} + O\left(P_{j,t}^{\phi} m_{j,t}/(|I_j| D_{i,t})\right)^2.
\end{aligned}$$

Note that if the technology exhibits constant returns to scale, we have

$$\frac{\lambda_j^{\frac{\gamma(1-1/\phi)}{1-(\alpha+\beta)(1-1/\phi)}}-1}{(\phi+(\alpha+\beta+\gamma)(1-\phi))\log\lambda_i}=\frac{\lambda_j^{\frac{\gamma(1-1/\phi)}{1-(\alpha+\beta)(1-1/\phi)}}-1}{\log\lambda_i}.$$

Moreover, if i's customer firms are symmetric, we have

$$\frac{P_{j,t}^{\phi}m_{j,t}}{|I_j|D_{i,t}}=\frac{D_{i,t}-\chi_i Y_t}{D_{i,t}}\frac{1}{|O_i|}.$$

Furthermore, if the numbers of customers and suppliers are equal across firms and $\chi_i=1$, the expression is reduced to

$$\frac{1-\alpha(1-1/\phi)}{|O_i|}.$$

Thus, in the simplest case with constant returns to scale and symmetric firms and networks, the first-order effect of the lumpy investment of $j\in O_i$ on the probability of i's lumpy investment is

$$\frac{\lambda_j^{\frac{\gamma(1-1/\phi)}{1-(\alpha+\beta)(1-1/\phi)}}-1}{\log\lambda_i}\frac{1-\alpha(1-1/\phi)}{|O_i|}.$$

Similarly, we can derive the increase in spiking probability when firm i's supplier makes a lumpy investment. If $j\in I_i$, we have

$$\Pr(d_{i,t}=1\mid d_{j,t}=1)-\Pr(d_{i,t}=1\mid d_{j,t}=0)=\frac{-\alpha\left(1-\frac{1}{\phi}\right)(\log P_{i,t+1}-\log P_{i,t})}{\left(1-(\alpha+\beta+\gamma)\left(1-\frac{1}{\phi}\right)\right)\log\lambda_i}.$$

Note that $P_{i,t}$ is affected by $p_{j,t}$. Also, optimal $p_{j,t}$ satisfies

$$p_{j,t}=(D_{j,t}/y_{j,t})^{1/\phi}=D_{j,t}^{1/\phi}\left[\tilde{\omega}\left(A_{j,t})P_{j,t}^{\alpha}D_{j,t}^{(1-\gamma)/\phi}k_{j,t}^{\gamma}\right)^{\frac{1}{1-(1-\gamma)(1-1/\phi)}}\right]^{-1/\phi}.$$

Then, $p_{j,t}^{1-\phi}$ increases due to j's lumpy investment by a factor

$$\lambda_j^{-\frac{\gamma(1-\phi)}{\phi(1-(1-\gamma)(1-1/\phi))}}-1.$$

Then, we have, for $j \in I_i$,

$$\log P_{i,t+1} - \log P_{i,t} = \frac{\lambda_j^{-\frac{\gamma(1-\phi)}{\phi(1-(1-\gamma)(1-1/\phi))}} - 1}{(1-\phi)|I_i|} \left(\frac{p_{j,t}}{P_{i,t}}\right)^{1-\phi} + O\left(1/|I_i|\right)^2 .$$

3 Data

This paper combines Japanese business survey and production network data provided by TOKYO SHOKO RESEARCH, LTD. (TSR). The survey (Basic Survey of Japanese Business Structure and Activities conducted by the Ministry of Economy, Trade and Industry) collects data from firms with 50 or more employees and 30 million yen or more capital. In 2022, 44812 firms were asked to participate in the survey, with a 90.2% response rate. We first use an unbalanced panel data set with an annual frequency covering 2007 to 2021. The number of firms is 31197. We define an investment spike as an indicator variable that takes the value of one when the investment–capital ratio exceeds 0.2. We take the spike dummy's time-series average to compute each firm's spike rate. The mean spike rate across firms is 0.135, and its standard deviation is 0.216. The median is 0, so we observe no investment spikes for more than half of the firms during the sample period.

We construct supplier–customer network data using the TSR database following the methodology described in Carvalho et al. (2021). We use the corporate number issued by the National Tax Agency as a key to merge the network data with the survey data. Each firm's average number of suppliers and customers over time is computed as follows: Among the 31197 firms in the survey, 28970 firms reported the number of suppliers and 26771 firms reported the number of customers at least once in the TSR data. In the TSR data, the cross-firm mean of the average number of suppliers is 23.3, and the median is 11.1. The heterogeneity is so considerable that the standard deviation is 66.3. Only firms with more than 50 employees were observed among these suppliers in the survey. In the following analysis, we count suppliers and customers only if they are in the survey. In this dataset, the cross-firm mean of the average number of suppliers is 5.75, and the median is 3.25, with a standard deviation of 13.88.

Similarly, the cross-firm mean of the average number of customers in TSR is 29.8, and the median is 11, with a standard deviation of 99.9. The cross-firm mean of the average number of customers in the survey is 6.30, and the median is 3.92, with a standard deviation of 12.8.

Figure 1 shows the time series of the aggregate variables in the dataset. Total investment indicates the aggregate investments (tangible and intangible) across firms in each period. The lumpy investment shows the investments aggregated over firms that exhibited an investment spike in the year. The left panel shows the levels of aggregate investments. The lumpy investment accounts for a sizable portion of total investments. The ratio of lumpy investment to total investment is 33% on average for the sample period. The right panel shows the growth rates of the total investments and lumpy investments, along with the growth rate of smooth investments, defined as the total minus the lumpy investment. We note a clear comovement of the lumpy and total growth rates. The coefficient of correlation is more than 95%, while the coefficient of correlation between the smooth and total growth rates is 29%, indicating the importance of lumpy investments in driving the total investment, as noted by many authors (Cooper and Haltiwanger (1996); Licandro

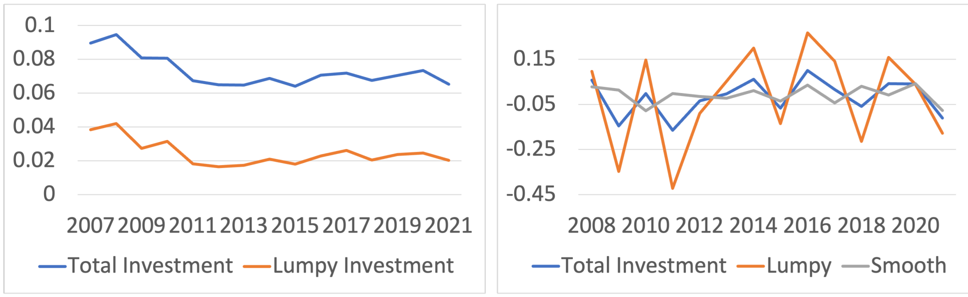

Figure 1: Aggregate investments over sample period

et al. (2006); Gourio and Kashyap (2007); Tanaka and Miyagawa (2009)).

4 Estimation

We estimate Equation (8) using a logit or linear probability model, where the dependent variable is the binary indicator of an investment spike. The independent variables are the fractions of supplier and customer firms that exhibit investment spikes. In addition, profit rate and liquidity are included as control variables. The profit rate is calculated by dividing gross profits (sales minus production costs) by outstanding capital stock (including tangible and intangible). The profit rate is considered a proxy for productivity in (8). We measure liquidity using the ratio of a firm's liquid assets to its capital stock. The summary statistics of the dependent variables are shown in Table 1. The median fraction of investment spikes in the firm's suppliers is 0.054, and that in the firm's customers is 0.068. The median profit rate is 0.159, and the median ratio of liquid assets to capital stock is 1.638.

Table 2 shows our main estimation result of the logit regression coefficients with firm fixed and year fixed effects. In specification (1) shown in

	median	mean	st. dev.
Fraction of spiking suppliers	0.054	0.088	0.125
Fraction of spiking customers	0.068	0.106	0.140
Profit rate	0.159	0.429	3.825
Liquidity	1.638	5.337	40.20

Table 1: Summary statistics of the independent variables

the first column, only the contemporaneous fractions of spiking customers and suppliers are included in the explanatory variables, whereas the second includes lagged fractions. The third column shows the result when the firm fixed effect is replaced with an industry fixed effect, increasing the sample size. There are 174 distinct industries in the sample. The coefficients show an increase in the odds ratio when the explanatory variable is increased by 1. We observe significant positive effects for all contemporaneous fractions. The lagged fractions are also significantly positive when the sample size is increased using the industry fixed effect. The magnitude of the coefficients is consistent across the specifications. We find that the effect of lagged liquid assets is significantly positive, which is consistent with the empirical studies on investment functions that find that firms need sufficient liquidity before investment (Fazzari et al. (1988); Hoshi et al. (1991); Whited (1992)). The lagged profit rate exhibits nonsignificant effects, whereas it is significantly positive in specifications that exclude liquidity.

Table 3 shows the estimates of the same logit regression with balanced panel data. The estimated coefficients for the spiking fractions of trading partners are largely consistent with those of the unbalanced panel in Table 2,

	(1)		(2)		(3)	
Customer	1.17***	(.061)	1.16***	(.064)	1.21***	(.063)
Customer (lag)			1.06	(.058)	1.12**	(.057)
Supplier	1.12**	(.062)	1.15**	(.067)	1.24***	(.069)
Supplier (lag)			1.10*	(.063)	1.20***	(.065)
Profit (lag)	1.0007*	(.0021)	1.0009	(.0021)	1.0023	(.0021)
Liquidity (lag)	1.0018***	(.0005)	1.0017***	(.0005)	1.0029***	(.0004)
Year FE	✓		✓		✓	
Firm FE	✓		✓			
Industry FE					✓	
N firms	9,487		9,014		22,321	
N obs	97,594		91,744		194,297	

Table 2: Logit estimates (odds ratio) of a firm's investment spike.

while the significance levels of some variables are lower because of the smaller sample size. A difference from the estimates in the unbalanced panel is the increased estimates for lagged profits, but they are nonsignificant except for specification (3).

Table 4 shows the results of the same regression with a linear probability model. The coefficients in the linear probability model show the impact of a trading partner's spike on a firm's spiking probability. The coefficients again show the same significance pattern as before. The estimates are comparable with those of spike probability we infer from the logit estimates, as discussed below.

In summary, the estimates in Tables 2–4 show that the likelihood of a

	(1)		(2)		(3)	
Customer	1.20*	(.131)	1.18	(.129)	1.21*	(.131)
Customer (lag)			1.16	(.124)	1.20*	(.127)
Supplier	1.30**	(.153)	1.26**	(.149)	1.30**	(.151)
Supplier (lag)			1.31**	(.150)	1.38***	(.153)
Profit (lag)	1.0129	(.0093)	1.0131	(.0093)	1.0240**	(.0096)
Liquidity (lag)	1.0013	(.0011)	1.0013	(.0011)	1.0022**	(.0011)
Year FE	✓		✓		✓	
Firm FE	✓		✓			
Industry FE					✓	
N firms	2,687		2,687		5,587	
N obs	34,931		34,931		72,492	

Table 3: Logit estimates (odds ratio) of a firm's investment spike with balanced panel data.

firm's investment spike positively depends on the investment spikes of its trading partners. The positive correlation was statistically significant and robust to estimation methods and samples.

5 Implications for the aggregate investment

Using these estimates, we can infer the impact of an investment spike over the production network as follows. Let p_I and p_O denote the probability of an induced investment spike for a supplier firm's and a customer firm's spike, respectively. Also, let $L.p_I$ and $L.p_O$ denote the probability of the investment

	(1)		(2)		(3)	
Customer	.016***	(.0044)	.015***	(.0047)	.020***	(.0047)
Customer (lag)			.006	(.0046)	.015***	(.0046)
Supplier	.011**	(.0046)	.013***	(.0049)	.029***	(.0050)
Supplier (lag)			.010**	(.0048)	.024***	(.0049)
Profit (lag)	.0003	(.00018)	.0003	(.0002)	.0008***	(.0002)
Liquidity (lag)	.0003***	(.00004)	.0002***	(.0000)	.0004***	(.0000)
Year FE	✓		✓		✓	
Firm FE	✓		✓			
Industry FE					✓	
N firms	23,224		22,326		22,326	
N obs	205,052		194,366		194,366	

Table 4: Estimates of the linear probability model of a firm's investment spike.

spike for a partner's lagged spike, respectively.

Suppose firm i spikes. The number of firms directly affected by the spike is $|I_i| + |O_i|$. The spike increases the probability of each customer spiking by $p_O/|O_i|$ and of each supplier by $p_I/|I_i|$ contemporaneously, and with one period lag by $L.p_O/|O_i|$ and $L.p_I/|I_i|$. Note that the p's are normalized by the number of i's trading partners, because the explanatory variables in the regressions are normalized as such, which is consistent with the propagation probability derived in our model in Section 2.3.

If the probability of a spike is independent across suppliers and customers, which holds if the gap between a firm's capital and its threshold is independent of each other, the average *number* of customers and suppliers that spike is p_I and p_O, respectively, because there are $|I_i|$ suppliers and $|O_i|$ customers. Because there are also lagged effects, the average number of total firms that are induced to make lumpy investment by a firm is $p = p_I + p_O + L.p_I + L.p_O$.

Specifically, let us consider the estimates of the third column in Table 4. Then, we obtain the probability of the induced investment spike to be $p = 0.088$. If we use the estimates in Table 2, we need to translate the increase in the odds ratio to an increase in probability. The marginal effects p_I, p_O, $L.p_I$, and $L.p_O$ are computed as 0.034, 0.037, 0.024, and 0.014, respectively. These estimates are consistent and slightly greater than the results from the linear probability model in Table 4. We use estimates from the linear model as a conservative estimate.

Correlating spiking investments can cause fluctuations in aggregate investments in several ways. First, a stochastic chain reaction in a homogenous network can generate aggregate fluctuations even when the underlying states of firms are independent. Second, chain reactions interacting through local network structures such as cliques amplify the aggregate fluctuations. Third, the heterogeneity of degrees augments aggregate fluctuations. Finally, the correlated states of firms contribute to aggregate fluctuations. The final route is possible because firms' states are coupled by the strategic complementarity of investments, as shown in the model. We leave this for future research and here concentrate on the first route where firms are homogeneous and firms' states are independent.

Suppose that there are n firms. Each firm i draws state s_i independently from a unit distribution function. Using Equation (7), we determine that firm i conducts an investment spike even without any trading partners conducting investment spikes. Then, firms' fraction $E[|\log(1-\delta_i)/\log\lambda_i|]$ spikes because of capital depreciation. In our back-of-the-envelope exercise, we assume homogeneous firms with common $\bar{\delta}$ and $\bar{\lambda}$. In our sample, the mean and median of λ_i conditional on $\lambda_i > 1.2$ (our definition of lumpy investment) are 1.502 and 1.314, respectively. We set $\bar{\lambda}$ to the mean (1.502) to represent the average impact of lumpy investments. Each investment spike will have a spillover effect on p trading partners on average. Hence, the sum of spikes induced by the deprecation and the multiplier effect is on average $(|\log(1-\bar{\delta})|/\log\bar{\lambda})/(1-p)$. We calibrate this variable to the average spiking rate observed in our sample, $f = 0.135$. Thus, $\bar{\delta}$ is identified by the equation $f = |\log(1-\bar{\delta})/\log\bar{\lambda}|/(1-p)$. Using $\bar{\lambda} = 1.502$ and $p = 0.088$, this yields $\bar{\delta} = 0.0489$.

In this setup, the number of firms induced to spike due to capital depreciation, say m, follows a binomial distribution with probability $\mu := f(1-p)$ and population n. Each firm in m has a multiplier effect, which is assumed to be independent across firms in m. Let L denote the total number of spiking firms, including m, and L^1 denote L conditional on $m = 1$. Using the variance decomposition formula, we have $V(L) = E[V(L \mid m)] + V(E[L \mid m]) = E[m]V(L^1) + V(m)E[L^1]^2 = \mu n V(L^1) + \mu(1-\mu)nE[L^1]^2$.

Moreover, we make a simplifying assumption that a firm's downstream and upstream firms never overlap. This is the case in a random graph with infinitely many nodes. Furthermore, we approximate the binomial distribution of the induced spikes per firm by a Poisson distribution with the same mean, which holds asymptotically as $|O| + |I|$ tends to infinity. Under this approximation, the propagation process of a firm's spike follows a Poisson branching process in which each spike induces trading partners' spikes, following a Poisson random variable Q with mean p. The sum of the Poisson branching process from the start until the process ends with 0 corresponds to L^1. Thus, $E[L^1] = 1/(1-p)$. Also, L^1 follows the same distribution as one plus Q-times convolution of L^1. Hence, $V(L^1) = E[QV(L^1)] + V(QE[L^1]) = pV(L^1) + pE[L^1]^2$, resulting in $V(L^1) = p/(1-p)^3$ (also see Nirei and Scheinkman (2024)). Combining with the previous result, we approximately obtain $V(L)$ to be $\mu np/(1-p)^3 + \mu(1-\mu)n/(1-p)^2$.

If we let the aggregate capital be $\bar{K}$, the aggregate lumpy investment is $(\bar{\lambda}-1)L\bar{K}$, whereas the steady-state level of aggregate investment is $\bar{\delta}\bar{K}$. Hence, the volatility of the aggregate investment's deviation from the steady state is $Std((\bar{\lambda}-1)L/(\bar{\delta}n))$. We compute this using the benchmark estimates from the third specification in Table 4: $p = 0.088$ and $n = 22326$. Combining with $\bar{\lambda} = 1.502$ and $f = 0.135$, implying $\bar{\delta} = 0.0489$ in the model, we obtain the aggregate investment volatility in our model as $Std((\bar{\lambda}-1)L/(\bar{\delta}n)) = 0.0261$. This amounts to 32% of the standard deviation of the aggregate investment growth rate in the data, which is 0.0812.

Note that this estimate is derived under the restricting assumption of a homogeneous network with nonoverlapping propagations, lowering the volatility. Hence, our back-of-the-envelope calculation suggests the potential importance of the complementarity of lumpy investments in generating aggregate investment fluctuations.

6 Conclusion

This study presents evidence of strategic complementarity for a firm's investment spikes. We first present a general equilibrium model with an input-output network of firms and indivisible capital investments. The model determines steady-state wages and returns to capital and derives the firm's optimal threshold policy for an investment spike. The policy function determines the probability of an investment spike as a function of the spikes of the firm's suppliers and customers, which provides an estimation equation for the complementarity of investment spikes between firms linked by intermediate input transactions.

We use the firm-level panel data and the firm-level transaction network data of Japanese firms to estimate the probability of an investment spike when a firm's trading partner exhibits an investment spike. By controlling for firm-level fixed effects, the contemporaneous investment spikes of trading partners generate positive impacts on the likelihood of a firm's investment spike with statistical significance. Significantly positive impacts extend to the lagged investment spikes of partners under the industry fixed effect specification. The impacts are quantitatively nontrivial, as the total average number of investment spikes caused by an investment spike is estimated to be 0.088.

References

Caballero, R. J. and E. M. Engel (1991). Dynamic (S,s) economies. *Econometrica 59*, 1659–1686.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply chain disruptions: Evidence from the Great East Japan earthquake. *Quarterly Journal of Economics 136*, 1255–1321.

Cooper, R. and J. Haltiwanger (1996). Evidence on macroeconomic complementarities. *Review of Economics and Statistics 78*, 78–93.

Cooper, R., J. Haltiwanger, and L. Power (1999). Machine replacement and the business cycles: Lumps and bumps. *American Economic Review 89*, 921–946.

Doms, M. and T. Dunne (1998). Capital adjustment patterns in manufacturing plants. *Review of Economic Dynamics 1*, 409–429.

Fazzari, S. M., R. G. Hubbard, and B. C. Petersen (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity 1988*, 141–195.

Gourio, F. and A. K. Kashyap (2007). Investment spikes: New facts and a general equilibrium exploration. *Journal of Monetary Economics 54*, 1–22.

Guiso, L., C. Lai, and M. Nirei (2017). An empirical study of interaction-based aggregate investment fluctuations. *Japanese Economic Review 68*, 137–157.

Hoshi, T., A. Kashyap, and D. Scharfstein (1991). Corporate structure, liquidity, and investment: Evidence from Japanese industrial groups. *Quarterly Journal of Economics 106*, 33–60.

Licandro, O., L. A. Puch, and M. R. Maroto Illera (2006). Innovation, machine replacement and productivity. *CEPR Discussion Paper Series 5422*.

Nirei, M. (2015). An interaction-based foundation of aggregate investment fluctuations. *Theoretical Economics 10*, 953–985.

Nirei, M. and J. A. Scheinkman (2024). Repricing avalanches. *Journal of Political Economy*. forthcoming.

Tanaka, K. and T. Miyagawa (2009). Do large scale investments improve corporate performance? (in Japanese). *RIETI Discussion Paper Series 09-J-032*.

Whited, T. M. (1992). Debt, liquidity constraints, and corporate investment: Evidence from panel data. *Journal of Finance 47*, 1425–1460.