Online Appendix

Appendix A: Variables definition

- **Sales:** Net sales [SALE in Compustat], deflated by the 4-digit industry-level deflator. We obtain the deflators from the NBER-CES Manufacturing Industry Database.
- **Capital:** Gross property, plant, and equipment, deflated by the price deflator for investment. Since investment is made at various times in the past, it would be imprecise to use the current year's capital deflator. To deflate capital stock, we use the method adopted by Brynjolfsson and Hitt (2003). In this method, we deflate capital stock at the calculated average age of capital. To calculate the average age of capital stock, we divide *accumulated depreciation* by *current depreciation*, from Compustat.
- **Materials:** Total expenses minus labor expenses. Total expenses is equal to sales minus operating income before depreciation and amortization. We obtain *Operating Income* from item 13 in Compustat. The resulting value is deflated by the 4-digit deflator for materials.
- **Labor expense:** To proxy for labor expense we use sector-average labor cost per employee, and multiply it to the total number of employees. To determine the average sector labor cost, we use the annual sector-level wage data (salary plus benefits) from the Bureau of Labor Statistics. Labor expense is deflated by the price index for total labor compensation.
- **Value added:** Sales (deflated) - Materials (deflated).
- **Capital investments:** Capital expenditures, from Compustat, deflated by the 4-digit industry-level deflator.
- **Firm age:** Proxied by the year the firm first appeared in Compustat.
- **Firm size:** Measured by the natural logarithm of total assets, from Compustat.
- **Geographic regions:** Constructed by using the headquarters' location of each firm.
- **Financial leverage:** Measured as the ratio of total debt (short-term debt + long-term debt) to the book value of total assets.
- **Financial liquidity:** Measured as the ratio of liquid assets to current liabilities, from Compustat.
- **Financial agility (Asset turnover):** Defined as the ratio of sales to total assets, from Compustat.
- **Inventory turnover:** Ratio of *cost of goods sold* to *inventory*.
- **Capital-to-labor ratio:** Defined as the ratio of capital expenses to labor expenses.
- **Diversification:** Number of business segments.

Appendix B: TFP and the Olley-Pakes Approach

When we estimate TFP through OLS, the resulting estimates are likely to suffer from simultaneity and selection biases. A simultaneity bias arises because there is systematic correlation between the input factors and the error term. A selection bias arises because a firm's profitability is correlated to its level of capital stock, which is fixed in the short term.

To deal with these problems, Olley and Pakes (1996) introduced a semi-parametric specification that controls for both biases; Keller and Yeaple (2009) later adapted this model using Compustat data. This approach uses capital investments, I_{it}, as a proxy variable, and makes the following assumptions (which are grounded on empirical results – see Olley and Pakes 1996):

1. Labor (l_t) is a variable factor at time t.
2. Capital (k_{it}) is a fixed factor at time t, and a function of the productivity level at $t-1$, i.e. $k_{it} = k\,(TFP_{i,t-1})$.
3. I_{it} is a function of TFP_{it} and k_{it}, i.e. $I_{it} = I\,(TFP_{it}, k_{it})$. This function satisfies $\frac{\partial I_{it}}{\partial TFP_{it}} > 0$ for any $I_{it} > 0$.

By assumption 3, we have that $TFP_{it} = h\,(I_{it}, k_{it})$, where h is the inversion of I. Therefore, we can re-write equation (1) as

$$y_{it} = \beta_l l_{it} + \phi_{it}\,(I_{it}, k_{it}) + \varepsilon_{it}$$

where $\phi_{it}\,(I_{it}, k_{it}) \equiv h\,(I_{it}, k_{it}) + \beta_k k_{it}$.[13] Note that ϕ isolates TFP, which is the source of the simultaneity bias. For this reason, we can estimate y_{it} and obtain consistent estimates for β_l. Although ϕ is unobservable, we estimate this function by using a third-order polynomial expansion on I and k, i.e. $\phi_{it}\,(I_{it}, k_{it}) \approx c_0 + \sum_{m=0}^{3}\sum_{n=0}^{3} c_{mn} k_{it}^m I_{it}^n$. This estimation yields estimates β_l^{OP} and $\hat{\phi}_{it}$.

Second, we estimate β_k. To this end, let $\Delta TFP_{it} \equiv TFP_{it} - TFP_{i,t-1}$ and assume that $cov(k_{it}, \Delta TFP_{it}) = 0$. Thus,

$$\begin{aligned} y_{it} - \beta_l^{OP} l_{it} &= \beta_k k_{it} + TFP_{it} + \varepsilon_{it} \\ &= \beta_k k_{it} + TFP_{i,t-1} + \Delta TFP_{it} + \varepsilon_{it} \\ &= \beta_k k_{it} + \hat{\phi}_{i,t-1} - \beta_k k_{i,t-1} + \Delta TFP_{it} + \varepsilon_{it} \end{aligned}$$

where $\hat{\phi}_{i,t-1} - \beta_k k_{i,t-1}$ is an unbiased estimate of $TFP_{i,t-1}$.

Now, define $\underline{TFP}_{it}(I_{i,t-1}, k_{it})$ as the productivity threshold for which a company is indifferent between exiting the market and running operations. Also, assume that the probability of survival of firm i, P_{it}, is a function of $TFP_{i,t-1}$ and $\underline{TFP}_{i,t-1}$. To estimate P_{it} we run a probit regression on a third order polynomial expansion on: (i) $I_{i,t-1}$, (ii) $k_{i,t}$, and (iii) the firm's age.

We use the estimated survival probability, $\hat{P}_{it}$, to estimate $y_{it} - \beta_l^{OP} l_{it} = \beta_k k_{it} + g\left(\hat{\phi}_{i,t-1} - \beta_k k_{i,t-1}, \hat{P}_{it}\right) + \Delta TFP_{it} + \varepsilon_{it}$, where $g\,(\cdot)$ is an unknown function. To approximate this function, we use a third order polynomial expansion on its parameters, where $g\left(\hat{\phi}_{i,t-1} - \beta_k k_{i,t-1}, \hat{P}_t\right) \approx c_0 + \sum_{m=0}^{3}\sum_{n=0}^{3} c_{mn}\left(\hat{\phi}_{i,t-1} - \beta_k k_{i,t-1}\right)^m \hat{P}_{it}^n$.

[13] For simplicity of exposition, we ignore industry fixed effects; in the actual calculation we include this type of control.

This allows us to obtain β_k^{OP}. We use β_l^{OP} and β_k^{OP} to derive the firm's productivity, where,

$$TFP_{it} = y_{it} - \beta_k^{OP} k_{it} - \beta_l^{OP} l_{it}$$

Appendix C: Robustness checks

C.1) Robustness checks on productivity estimation

- Alternative industry classification: Productivity is the relative efficiency ranking of a firm within the industry it operates and, as a result, any productivity estimate is sensitive to the classification scheme used to group firms into industries. To avoid inconsistencies across studies, the literature often uses the Standard Industry Classification (SIC) code. We follow this standardized approach by using a 2-digit SIC code. To ensure, however, that our main conclusions are not sensitive to this classification, we re-estimated our results by using a 3-digit and a 4-digit SIC code. We also used a 2-digit North American Industry Classification System (NAICS) code. We find that our estimates are robust to these alternative classifications.
- Alternative specification: The classic Cobb-Douglas production function, $Y = AK^{\beta_K} L^{\beta_L}$, has two input choices: capital (K) and labor (L). It is not uncommon, however, to find different specifications for this function. A popular alternative includes, in addition to labor and capital, a third input that measures *intermediate materials* (M). Under this specification the Cobb-Douglas function becomes $Y = AK^{\beta_K} L^{\beta_L} M^{\beta_M}$.

  There is no inherent advantage to using either functional form, and our choice was motivated by related literature which, typically, uses a two-factor functional form (e.g. Imrohoroglu and Tuzel 2014; Kellogg 2011; and Van Biesebroeck 2005).

  We re-estimated our results by using a three-input production function, and found that the estimated input elasticities are $\hat{\beta}_K = 0.368$, $\hat{\beta}_L = 0.470$ and $\hat{\beta}_M = 0.226$. We used the resulting estimates to perform a visual comparison of the firm's productivity under both types of functions. The relative ranking of firms does not seem to be affected by the choice of a 2-input or a 3-input production function. In other words, productive firms look productive (and unproductive firms look unproductive) regardless of the specification used. In the actual estimation of spillover effects, our results preserve their qualitative properties.

C.2) Robustness checks in the estimation of spillover effects

- Unweighted data: In the base model we assumed that the strength of a supplier-customer relationship is proportional to the value of their sales; this raises the question about how sensitive are the results to variation in the weights – as opposed to variation in the variables of interest. To study this issue we have re-estimated our results by weighting all relationships equally.

  The estimates obtained by using an unweighted relationship are qualitatively similar to the weighted estimates. In particular, the endogenous effect is almost identical (i.e. the effect decreases from 0.574 to 0.562, and is still significant at the 1% level), whereas the contextual effects don't vary in sign – these effects, however, decrease in absolute magnitude.

		coeff.	*t-stat*
Endogenous effect (ω)	Customer's TFP	0.562***	4.15
Contextual spillover effects (θ)	Fin. leverage	0.001	0.11
	Fin. liquidity	0.099***	4.00
	Fin. agility	0.051***	4.84
	Inv. turnover	0.017	0.76
	Capital labor ratio	-0.005	-0.28
	Diversification	0.064*	1.66
	Age	-0.002	-0.15
	Size	0.068***	3.08
	Region: West	-0.106*	-1.73
	Region: Midwest	0.099***	2.84
	Region: Northeast	0.134***	4.42
	Region: South	0.066*	1.93

Table 15 Spillover effects with unweighted data

Weighting the relationships through sales allows us to capture the strength of the relationship with some detail. Because of this, we were expecting to find a slight decrease in the magnitude of most contextual coefficients. None of the effects exhibited a statistically significant change in sign.

- Alternative variable definitions: We relied on standard accounting definitions to define the vector of characteristics, $\mathbf{X}_i$. But there are multiple (valid) definitions for some characteristics. Our modus operandi was to adopt the most commonly used definition (in related literature); in other cases the choice was data-driven. To ensure that our main results are robust to the choice of definition, however, we re-estimated these results by using the following alternative definitions:
  — *Operational characteristics:* We defined *inventory turnover* as the ratio of cost of goods sold to inventory. We re-estimated our results by using the sales/inventory ratio, and the result was unaltered. As a robustness check for the level of *Diversification*, we used a dummy variable to distinguish between specialized firms (only one business segment) and conglomerates (those firms that report multiple business segments). Under this alternative definition, the coefficient estimate jumps from 0.010 to 0.042 (and becomes significant at the 10% level).
  — *Financial characteristics:* To measure financial leverage, we used the ratio of total debt (short-term plus long-term debt) to total assets. But, in some studies, leverage is measured by exclusively using the firm's long-term debt in the numerator (e.g. Imrohoroglu and Tuzel 2014). In other studies, leverage is measured by using the ratio of book value of total assets to the book value of equity (e.g. Patatoukas 2011). We re-estimated our results using these alternative definitions. The quantitative results are not altered by either definition, mainly due to the fact that the alternative definitions are highly correlated with the original definitions. To measure financial liquidity, we used the quick ratio in our main model. We also defined liquidity by using the current ratio (assets over liabilities) and the cash ratio (cash/liabilities).

Other characteristics, including the level of accounts payable and accounts receivable, were not considered due to the high degree of missing data.

— *Idiosyncratic characteristics:* We could control for geographic effects by dividing firms into states, or into one of the nine Census-Bureau designated divisions. We found that using the official census regions (West, Mid-West, South, North East) facilitates the exposition of our analysis, as opposed to dividing firms into states, and analyzing the separate impact of each dummy variable. If we re-estimate our results by classifying firms into their home states, our results are qualitatively similar. As an aside, it is worth noting that states like California, New York, and New Jersey have the most productive firms (on average).

C.3) Robustness checks for Section 7: the impact of relationship structure

- Maturity extension: A possible concern with our results is the fact that our data is truncated at the 10% revenue level. This implies that we could be missing entries from firms that have weak linkages, i.e. near the 10% threshold. This truncation could generate gaps that lead us to misrepresent the true maturity of the relationship. As a case in point, consider a relationship that is reported at years t and $t-2$, but not at year $t-1$. If the weight of this relationship is close to the 10% level at either years $t-2$ or t, then it is likely that the missing year $(t-1)$ is an artifact of the data truncation.

  Fortunately, we found that only 4.3% of the dyadic relationships have gaps, and approximately half of these gaps could be attributed to “low” weights (i.e. less that 15 percent in the years surrounding the gap).

  We performed two checks. First, we re-estimated our results by filling for the gaps that are characterized by low weights. We also defined maturity as the *overall* number of years the firms have interacted (instead of using the number of *consecutive* years). The results are almost identical in these two robustness checks. This is likely due to the fact that only a small fraction of the relationships have gaps.

  Another issue with our results is that the sub-sample size decreases with the level of maturity. This could lead to the possibility that the drop in estimation power can be an alternate explanation for the observed results. As a robustness check, we re-estimated our results by including *only* the approximately 2,000 dyads that are found across each of the maturity levels (this captures approximately 37% of the sampled dyads). We found the same pattern of results across this sub-sample. Nonetheless, the results in the medium maturity levels seem to spike less. This could lead us to conclude that, although the main conjecture of this section still holds (i.e. the endogenous effect is inverse U-shaped as a function of maturity), in reality the variation in the estimates is less pronounced than as shown in Table 8.

Effect	*Variable*	*Years 1-2* coeff.	*Years 1-2* t-stat	*Years 3-4* coeff.	*Years 3-4* t-stat	*Years 5-6* coeff.	*Years 5-6* t-stat	*Years* ≥ 7 coeff.	*Years* ≥ 7 t-stat
Endogenous effect (ω)	Customer's TFP	0.245	1.21	0.556**	2.01	0.463*	1.79	0.117	0.68
Contextual spillover effects (θ)	Fin. leverage	-0.122**	-1.91	-0.006	-0.64	-0.014	-0.42	-0.012	-0.29
	Fin. liquidity	0.161***	2.68	0.095	1.31	0.083	0.89	0.093**	2.14
	Fin. agility	0.114***	2.41	0.079*	1.72	0.084*	1.85	0.119***	3.52
	Inv. turnover	0.084	0.85	0.010	0.11	-0.140	-1.28	0.173***	2.77
	Capital labor ratio	-0.169	-0.93	-0.150	-0.90	-0.170	-1.15	0.080	0.66
	Diversification	0.132	0.70	-0.015	-0.08	0.014	0.28	0.274	1.14
	Age	0.169	0.98	0.316	1.57	0.221	1.12	-0.070*	-1.73
	Size	0.087	0.83	0.001	0.01	0.307***	4.09	-0.095*	-1.85
	Region: West	0.063	0.36	-0.118	-0.66	-0.130	-0.68	-0.124	-1.02
	Region: Midwest	0.072	0.47	0.159	1.06	0.137	1.09	-0.022	-0.19
	Region: Northeast	0.271**	2.10	0.264**	2.14	0.252**	2.00	0.157	1.42
	Region: South	0.087	0.62	0.276**	2.16	0.144	1.19	0.1437	1.29

Table 16 Endogenous and contextual effects as a function of maturity, with restricted subsample (i.e. only including dyads that reach 7+ years of maturity)

- Concentration extension: A potential concern with the above results, again, is that the truncation in our data can affect the degree of concentration. We decided to run a robustness check to test this issue. In particular, we re-estimated our results using the Bloomberg dataset, which comprises a much richer customer database for the year 2013 (for more details about this database, see Appendix C.4). The levels of concentration, however, are practically unaffected by the data truncation. This is because of the nature of the Herfindahl index, which is highly invariant to small weights. Because of this, we found that the use of the Bloomberg dataset does not change the signs of the coefficients in our estimation.

C.4) Data truncation

A particular concern with our data choice is that the reports are truncated at the 10% level of revenue. In other words, if a customer represents less than 10% of a firm's revenue, it is missing from the data. This could lead to biases.

To ensure that our results are not an artifact of this data choice, we decided to perform two robustness checks. First, we artificially truncated the dataset from the 10% level (the default truncation) to the 30% level. We performed this truncation in 2% increment levels. We report the impact of the truncation on the endogenous effect in Figure 7. As one can observe from the figure, the endogenous effect and the truncation level are positively correlated. This makes sense; we expect that larger customers play a more important role on the suppliers. The impact of the truncation, however, only seems to cause a significant impact on the results when we truncate the reports above the 18% level. At the 10%-16% levels, the effect of the truncation is relatively minor.

Second, we gathered the Bloomberg dataset, which builds supply chain relationships by using information from multiple sources (including the 10-K filings). This allows Bloomberg to construct a network that is 10 times as dense (per firm) as our dataset. In particular, this dataset comprises more

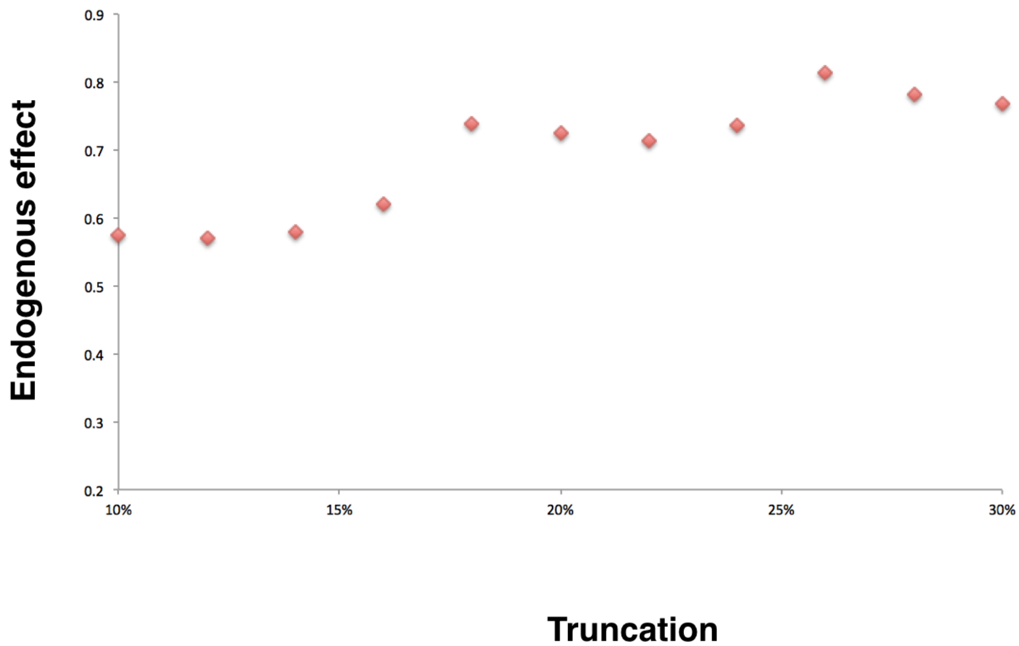

Figure 7 **The size of the endogenous effect as a function of various truncation levels**

than 10,000 measurable relationships. In comparison, our dataset includes slightly more than 1,000 relationships (on average) per year. A big drawback of the Bloomberg dataset is that it only reports cross-sectional relationships. This data limitation would have prevented us from drawing any dynamic inference on the nature of the spillover effects. For example, recall that to control for selection biases we use supply chain dynamics. Although the Bloomberg dataset would have prevented us from doing much of the analysis in the main model, it is a good dataset to gauge the robustness of our results.

We estimated and compared estimation results, from the model of Section 5.1.2, using (i) the Bloomberg database, and (ii) only the 10-K filings reported in Bloomberg. As it can be observed in Table 17, the results are highly insensitive to the inclusion of small customers. It may seem surprising that, although the Bloomberg database includes ten times as many reports, the results are almost identical. But this is mainly due to the fact that, below the 10% threshold, the Bloomberg reports include customers with insignificant weights. Specifically, the average weight of those customers not reported in the 10-K filings, but reported in Bloomberg, is 0.5%. So, although the Bloomberg database is a great resource for other types of studies where the data truncation is a pressing issue (e.g. for measuring connectivity or centrality), the impact of small customers is not significant for our purposes.

Effect	*Variable*	>10% filings *coeff.*	*t-stat*	Bloomberg *coeff.*	*t-stat*
Endogenous effect (ω)	Customer's TFP	0.528**	2.14	0.501**	2.05
Contextual spillover effects (θ)	Fin. leverage	-0.018	-0.57	-0.194	-1.27
	Fin. liquidity	0.418***	4.86	0.350***	3.58
	Fin. agility	0.093**	2.26	0.117***	3.27
	Inv. turnover	0.001	0.01	-0.023	-0.37
	Capital labor ratio	0.305*	1.93	0.319	1.22
	Diversification	0.064	0.32	0.049	0.85
	Age	0.041	0.67	0.001	0.03
	Size	-0.146*	-1.74	-0.149*	-1.66
	Region: West	-0.114	-0.49	-0.004	-0.02
	Region: Midwest	0.172	0.79	0.091	0.48
	Region: Northeast	-0.068	-0.45	-0.076	-0.54
	Region: South	0.124	0.79	0.148	0.45
Firm effects (γ)	Fin. leverage	0.035	0.14	-0.040*	-1.83
	Fin. liquidity	-0.113***	-3.86	-0.136***	-3.31
	Fin. agility	0.082**	2.15	0.057**	1.99
	Inv. turnover	0.023	0.89	-0.029	-1.05
	Capital labor ratio	-0.016	-0.76	-0.021	-1.50
	Diversification	-0.028	-0.14	-0.065	-0.24
	Age	0.041	1.20	0.053	1.57
	Size	0.115**	2.14	0.165***	3.34
	Region: West	0.036	0.46	-0.020	-0.17
	Region: Midwest	-0.094	-0.88	-0.009	-0.09
	Region: Northeast	0.007	0.08	-0.061	-0.62
	Region: South	0.035	0.77	0.096	1.06
Number of Observations		1,023		9,769	
Network Fixed Effects		Yes		Yes	
Selection covariance ($\sigma_{u\xi}$)		N/A		N/A	

*** p<0.01, **$p < 0.05$,*p<0.1

Table 17 In Column 1, we report estimates using the 10-K filings reported in Bloomberg. In Column 2 we report the estimates using the entire Bloomberg database.

C.5) Estimating Dynamic spillover effects

The endogenous spillover effect (ω) measures how a supplier's productivity is affected by the productivity of its customers. As such, ω captures the effect of, not only communication and collaboration with other firms, but also the effect of learning and mentoring.

An important issue here is that learning effects are not always internalized by the supplier immediately but, rather, they diffuse through time. In other words, it may take two to three years for a supplier to learn and adopt the productive practices of its partners. But our model does not capture these dynamic effects.

We test the robustness of our model by studying dynamic spillovers. In this extension, we assume that a firm's productivity affects its partners' productivity with a lag. We study the following model using the identification technique from Section 5.1.2:

$$\mathbf{TFP_t} = \beta\mathbf{1} + \mathbf{X_t}\gamma + \mathbf{W_t}\mathbf{X_t}\theta + \sum_{\mathbf{n=0}}^{\mathbf{N}} \omega_{\mathbf{t-n}}(\mathbf{W_{t-n}})\mathbf{TFP_{t-n}} + \mathbf{u_t}$$

We regressed various specifications of the above model by setting N equal to 1, 2, and 3 and found the presence of lagged effects. For example, by running a model with two lagged variables (i.e. by setting $N=2$), we found that the endogenous spillovers were equal to $\omega_t=0.531$, $\omega_{t-1}=0.120$, and $\omega_{t-2}=0.128$. Note that this sample includes only those firms that appear for three consecutive years (the sample size is equal to 9,259). All coefficients are statistically significant at the 1% level. If we drop the lagged effects, our regression (for this same sample) shows that $\omega_t=0.632$. Most other results are qualitatively identical under both regressions.

Our main conclusion is that our qualitative results are robust to the introduction of lagged endogenous effects. However, as we see above, the learning effects that diffuse through time are non-trivial. These effects should be analyzed in a more careful manner – in a separate study.

Appendix D: Additional tables

Summary Statistics

VARIABLES	(1) Mean	(2) Std. Dev.	(3) 25^{th} percentile	(4) 50^{th} percentile	(5) 75^{th} percentile	(6) 99^{th} percentile
TFP	1.770	0.618	1.503	1.772	2.069	3.295
Age	18.23	14.63	6	13	28	56
Leverage	3.637	162.7	1.457	2.042	2.964	24.47
Fin. liquidity	0.650	0.854	0.345	0.528	0.778	2.495
Total assets turnover	1.313	0.842	0.779	1.173	1.637	4.243
Inventory turnover	14.37	78.83	3.044	4.867	9.247	151.9
Capital-to-labor ratio	1.714	80.80	1.263	2.039	3.596	59.72
Region: West	0.217	0.412	0	0	0	1
Region: South	0.243	0.429	0	0	0	1
Region: Mid-West	0.214	0.410	0	0	0	1
Region: North-east	0.355	0.479	0	0	1	1
Total assets	4,994	19,176	41.37	256.2	2,009	83,232

Table 18 Table of summary statistics

	TFP	Fin. Leverage	Fin. Liquidity	Fin. Agility	Inv. Turnover	Capital-Labor ratio	Diversification	Age	Size
TFP	0.00	3.16***	2.52**	2.81***	3.00***	3.19***	3.07***	2.34**	2.94***
Fin. Leverage	-3.16***	0.00	-3.85***	-3.62***	-1.01	0.32	-0.21	-1.60	-1.50
Fin. Liquidity	-2.52***	3.85***	0.00	1.76*	2.60***	3.96***	2.39**	-0.05	2.27**
Fin. Agility	-2.81***	3.62***	-1.76*	0.00	1.60	3.70***	1.51	-0.73	1.12
Inv. Turnover	-3.00***	1.01	-2.60***	-1.60	0.00	1.23	0.43	-1.22	-0.40
Capital-Labor ratio	-3.19***	-0.32	-3.96***	-3.70***	-1.23	0.00	-0.38	-1.69*	-1.71*
Diversification	-3.07***	0.21	-2.39***	-1.51	-0.43	0.38	0.00	-1.36	-0.73
Age	-2.34***	1.60	0.05	0.73	1.22	1.69	1.36	0.00	1.06
Size	-2.94***	1.50	-2.27**	-1.12	0.40	1.71	0.73	-1.06	0.00

Table 19 Table of t-values that measure the statistical significance between the differences across the spillover coefficient. For example, we can observe that the t-test evaluating the difference between (i) the endogenous coefficient (TFP) and (ii) the coefficient for financial leverage yields a t-value of 4.34. This means that, the former coefficient is significantly larger, and this difference is significant at the 1 percent level.

	Low		Medium -Low		Medium -High		High	
	Mean	Std Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
TFP	0.042	1.142	-0.019	0.925	-0.046	0.739	-0.024	0.628
Age	0.311	0.975	-0.002	0.945	-0.304	0.982	-0.308	1.010
Size	-0.272	0.960	0.021	0.991	0.268	1.079	0.469	1.000
Fin. Leverage	-0.005	1.044	-0.026	1.036	0.061	1.019	0.012	0.726
Fin Liquidity	-0.036	1.116	-0.011	0.941	0.031	0.798	0.126	0.706
Fin. Agility	-0.040	0.970	0.001	0.998	0.035	0.989	0.119	1.098
Inv. Turnover	0.001	1.097	0.001	0.967	0.012	0.912	-0.013	0.682
Diversification	0.093	0.950	0.099	0.974	-0.099	1.078	-0.100	0.960
Input Intensity	-0.01	0.95	0.010	1.11	0.000	0.82	0.020	1.12
# of dyads	12,022		4,724		3,324		2,312	

Table 20 Summary for different maturity levels across the variables (which have been standardized across the entire sample to fit a standard normal distribution).