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Claudia Custodio, Miguel Ferreira and Emilia Garcia-Appendini

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Abstract

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JEL Classification: G31, G32, G33, L11, L14

Keywords: financial distress, Economic distress, Real estate prices, Supply Chain

Claudia Custodio - c.custodio@imperial.ac.uk
Imperial College Business School and CEPR

Miguel Ferreira - miguel.ferreira@novasbe.pt
Universidade Nova de Lisboa and CEPR

Emilia Garcia-Appendini - emilia.garcia@uzh.ch
University of Zurich

The Economic Costs of Financial Distress*

Cláudia Custódio
Imperial College Business School, CEPR, ECGI

Miguel A. Ferreira
Nova School of Business and Economics, CEPR, ECGI

Emilia Garcia-Appendini
University of Zurich

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In the Modigliani and Miller (1958) perfect capital markets framework, capital structure decisions do not affect the value of a firm's assets, and therefore economic performance. However, in the presence of frictions, such as the costs of financial distress, capital structure decisions can have important economic consequences. A common challenge when estimating the costs of financial distress, in particular the indirect costs, is to disentangle economic distress from financial distress. Economic distress that is due to demand shocks can lead to financial distress if a firm does not generate enough cash flow to meet its financial obligations. But can financial distress lead to economic distress? In the presence of information asymmetry, contractual frictions, or other potential conflicts between the firm and its stakeholders, a firm facing financial distress might experience a reduction in the sales of its products and/or services. In this paper, we estimate the economic costs of financial distress.

There are different reasons why financial distress can lead to economic distress. First, customers might factor in higher risks of bankruptcy and reduce their exposure to failing firms (Titman (1984), Opler and Titman (1994)). This might be particularly pronounced for durable goods suppliers, because financial constraints, or more drastically bankruptcy, can compromise post-purchase client service and guaranties. Second, clients might be concerned that distressed suppliers may compromise the quality of their products, for instance by using lower quality materials or providing worse working conditions (Maksimovic and Titman (1991), Hanka (1998), Matsa (2011)). Third, suppliers might have to increase prices in the short run to overcome financial distress (Chevalier and Scharfstein (1996)). At the same time, low-levered suppliers might predate on their distressed competitors by offering lower prices, and clients may switch to these suppliers to benefit from larger mark-ups (Fudenberg and Tirole (1986), Bolton and Scharfstein (1990)). Finally, financial distress might have a negative effect on the reputation of a firm, which may lead clients to buy from other suppliers (Maksimovic and Titman (1991), Brown and Matsa (2016)).[1]

[1] An alternative hypothesis in the case of more specific goods is that clients increase purchases to build up inventory for precautionary reasons, or even to bail out a strategic supplier because switching to another supplier is not

We use a client-supplier pair panel sourced from the Compustat Segment database for the 2000-2015 period to estimate the decrease in sales that is caused by financial distress. To identify the effects of a supplier's financial distress on its sales, we use a difference-in-differences-in-differences (DDD) empirical design. Specifically, we exploit the variation in the value of corporate real estate assets (our measure of exposure to real estate shocks as proxied by the ratio of property, plant, and equipment to total assets) and leverage (our main measure of financial constraints as proxied by the ratio of total debt to total assets) in suppliers' balance sheets to determine the exposure to reductions in real estate prices (the treatment). Using a difference-in-differences (DD) approach, we compare firms with high real estate assets (treatment firms) to firms with low real estate assets (control firms) around declines in real estate prices. Using a DDD approach, we compare the DD estimates of high leverage firms with those of low leverage firms (i.e., our estimate of the indirect costs of financial distress).

Local real estate prices are arguably unrelated to the demand of a given product, except for the fact that they may affect the financial condition of a supplier that is exposed to the real estate market, especially when suppliers and clients are located in different counties. Moreover, shocks to real estate prices have the advantage of hitting the asset's side of the balance sheet as opposed to directly affecting its financing side, which could be linked to other endogenous financial polices. Real estate shocks have been shown to impact investment and financial policies through the collateral channel (e.g., Gan (2007), Chaney, Sraer, and Thesmar (2012), Cvijanovic (2014)), Therefore, we expect clients to respond to these shocks if they suspect the supplier may be in financial distress. When clients observe these shocks, and if the cost of switching suppliers is sufficiently low, they might reduce their exposure to this supplier for precautionary motives, even if financial distress does not materialize. When clients do not observe the shock to local real estate prices, they might still become aware a supplier is in financial distress; for example, they could experience a decrease in quality, or delays dispatching orders.

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feasible. Anecdotal evidence suggests that clients may bail out suppliers. PSA Group, the carmaker of the brands Peugeot and Citroen, agreed to contribute to a rescue plan for the struggling supplier GM&S, which consisted of a purchasing commitment of €60 million (*Reuters*, July 19, 2017).

Our baseline regression includes client-by-time fixed effects, which implies that identification comes from the variation in the value of real estate assets and leverage across different suppliers of the same client in a given year. To the extent that this within-client comparison absorbs client-specific changes in demand for products, the estimated difference in sales can be plausibly attributed to differences in suppliers' financial distress, rather than demand shocks. This identification strategy is similar to that commonly used in the banking literature in which the comparison is across banks (which suffer a liquidity shock) for the same borrower (e.g., Khwaja and Mian (2008)). Since clients are admittedly more likely to switch suppliers in the same industry, in some regressions we further interact the client-by-time fixed effects with supplier industry fixed effects to restrict the variation to suppliers within the same industry.

We find that clients reduce their purchases from suppliers in financial distress. They decrease their purchases from suppliers that are more affected by a decline in local real estate prices when compared to otherwise similar suppliers that are less affected by local real estate prices. Our estimates are economically significant: a supplier with a high exposure to real estate shocks suffers a 10% stronger reduction in sales when there is a drop in real estate prices in the county where it is located, relative to a supplier with low exposure to real estate shocks. Our results are particularly strong for the 2007-2009 financial crisis period when a supplier with high exposure to real estate shocks suffered a 30% stronger reduction in sales.

To further validate that demand-side factors are not driving our results, we consider regressions with supplier county-by-year fixed effects, which likely absorb county-specific shocks. We also show that the effect is more pronounced when clients and suppliers are located further away from each other in terms of geographical distance, and thus demand shocks affecting suppliers and clients are less likely to be correlated. In addition, we conduct a placebo test in which we use fictitious real estate shocks. We conclude that it is unlikely that local demand can explain the reduction in suppliers' sales to a given client.[2]

[2] The estimated difference in sales across suppliers of the same client could be a result of a client decision to reduce its exposure to a financially distressed supplier or a disruption in the supplier's production.

We perform additional tests by exploring the heterogeneity in the suppliers' industries. First, we examine whether the effect on sales is more pronounced in competitive industries. In more competitive industries, the effects of financial distress might be more severe, as clients might anticipate greater cuts in product quality or customer service, and a higher likelihood that the supplier exits the market. We find that the reduction in sales for financially distressed suppliers is indeed more pronounced in more competitive industries. The reduction in sales is larger in industries with more players, high 1 – Lerner Index, and when the suppliers have low market share and low net margins.

Second, we examine whether the effect of financial distress on sales is more pronounced when the supplier produces a more specific product and/or service. We employ three measures of the supplier's specificity: R&D expenditures, R&D output, and intangible assets. R&D expenditures and R&D output (as measured by patent counts) capture the importance of relationship-specific investments and restrictions on finding alternative material sources. Intangible assets are associated with a more specific and differentiated input. The estimated indirect costs of financial distress are larger when suppliers produce less specific goods, i.e., when the costs of switching suppliers are low. Finally, we check whether the reduction in sales is larger for suppliers that produce durable goods and operate in manufacturing industries. Our results are more pronounced for durable goods and for manufacturing industries, which is consistent with the idea that this type of goods typically require post-purchase service and clients might be concerned that the supplier will get liquidated and not be able to provide this service.

Finally, we focus on the relationship between suppliers and clients as proxied by the weight that the supplier represents of the client's cost of goods sold. If there is stronger dependence between client and supplier, it is more likely that the client attempts to reduce its exposure to avoid a potential disruption in the supplier's production. In alternative, clients may find it harder to substitute suppliers with whom they have a stronger relationship. We find that the decrease in a supplier's sales due to financial distress is more pronounced if the client is more dependent on the supplier, which is consistent with the notion that clients want to hedge against a disruption in a supplier's production.

Our baseline results are robust to alternative measures of real estate assets following Chaney, Sraer, and Thesmar (2012), and Campello, Connolly, Kankanhalli, and Steiner (2019). These are improved measures of the market value of the commercial real estate assets owned by firms and their exact locations. Because our identification strategy also relies on ex ante measures of financial constraints, we perform additional tests using the market value of leverage, the Kaplan-Zingales (KZ) index of financial constraints (Kaplan and Zingales (1997)), and the Merton's (1974) measure of distance to default. Our baseline results are robust to these alternative measures.

Overall, our results suggest that a supplier's financial distress driven by local real estate prices can lead to its economic distress as measured by a reduction in sales. Moreover, our results suggest that the indirect costs of financial distress are substantial, especially in a competitive environment and for manufacturers of durable goods. We conclude that the indirect costs of financial distress are sufficiently sizable to be an important consideration in capital structure decisions.

Our paper extends the discussion of how to disentangle financial distress from economic distress (Opler and Titman (1993, 1994), Denis and Denis (1995), Andrade and Kaplan (1998)) and estimate the economic impact of financial distress (Almeida and Philippon (2007), Hortacsu, Matvos, Syverson, and Venkataraman (2013), Nocke and Thanassoulis (2014), Giroud and Mueller (2017), Gilchrist, Schoenle, Sim, and Zakrajsek (2017), Kim (2018), Sautner and Vladimirov (2018)). We contribute to this literature by using client-supplier pairs data on a wide variety of industries and performing estimations with client-by-year fixed effects, which allows us to control for demand-side effects. We provide evidence of a causal effect of financial distress on economic performance driven by supply-side factors, and thus a cleaner measure of the indirect costs of financial distress. We estimate a reduction in sales of about 10%, which implies that the average indirect costs of financial distress are about 18% of firm value if we assume a price-to-sales ratio of 1.18 (the median in our sample). This estimate is line with previous research, which finds average indirect costs of financial distress between 6% and 20% of firm value.

Our paper is related to the literature on the impact of real estate prices on corporate investment (Chaney, Sraer and Thesmar (2012)), employment (Mian and Sufi (2014)), household debt (Mian and Sufi (2011)), small business employment (Adelino, Schoar, and Severino (2015)), and entrepreneurship (Schmalz, Sraer, and Thesmar (2017)). In addition, Cvijanović (2014) shows that leverage increases with collateral value. However, Campello, Connolly, Kankanhalli, and Steiner (2019) show that the relation between investment and real estate prices is not due to the value of collateral but to the high systematic risk exposure of real estate assets. We contribute to this literature by estimating the indirect costs of financial distress due to real estate shocks through the balance sheet channel.[3]

Our paper is also related to the literature on the role of a firm's balance sheet in the transmission of business cycle shocks (Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999)). Giroud and Mueller (2017) show that more highly levered firms exhibit significantly larger declines in employment in response to drops in local consumer demand (proxied by real estate prices) during the Great Recession. We contribute to this literature by showing that suppliers with weak balance sheets (i.e., highly levered firms) experience a more pronounced reduction in their sales in response to financial shocks.

I. Data and Methodology

A. Sample and Variables

Our sample consists of supplier-client pairs whose headquarters are located in the United States. To obtain supplier-client relationships, we rely on Statements of Financial Standards (SFAS) numbers 14 and 131. Under these reporting disclosures, publicly listed firms in the U.S.

[3] We use real estate prices as financial shocks, which should be valid regardless of whether the firm raises unsecured or secured debt following a rise in value of real estate assets. However, the effect of a drop in the value of real estate assets could be more pronounced if the firm holds more secured debt.

must disclose, on a yearly basis, the identity of clients and the sales to clients whose purchases represent more than 10% of total sales. We collect this information from the Compustat Segment database for 2000-2015. We identify the suppliers (using GVKEY) and retrieve the names of their clients. We use GVKEY to obtain financial data for the suppliers from Compustat. Using text-searching algorithms complemented with manual searches, we match the reported client names to Compustat data to obtain their balance sheet information. As we restrict the searches to publicly traded firms from Compustat, we are unable to identify clients that are private firms, governments, or firms based outside of the U.S. Similarly, the SFAS 14 and 131 reporting regulations limit our ability to identify clients that buy small amounts or aggregate clients. Table A.1 in the Appendix provides variable definitions.

In our estimations, we use real estate prices as shocks to the collateral value of firms that own real estate to estimate their sensitivity to economic and financial distress. Indeed, in the presence of incomplete contracts, lower collateral values affect the likelihood of a firm's financial distress by increasing its external financing premium, which acts to decrease its creditworthiness and borrowing capacity (Hart and Moore (1994)). Furthermore, this collateral channel is stronger for firms with low net worth and constrained firms (Bernanke and Gertler (1995), Chaney, Sraer, and Thesmar (2012)). Thus, the balance sheet strength of a firm should also play a key role in the transmission of financial distress to economic distress.

In order to evaluate a firm's economic distress, we use the supplier's leverage as our main measure of financial constraints and the changes in sales to each client, obtained from the Compustat Segment database. We use a firm's real estate assets to measure its exposure to real estate prices. Since information about corporate real estate assets is only available in Compustat until 1993, in our main estimations we use the book value of property, plant, and equipment (PPE) as a proxy for real estate assets. Corporate real estate assets account for more than 80% of PPE (Cvijanovic (2014)). Moreover, the ratio of PPE to total assets is highly correlated with the ratio of the book value of corporate real estate assets to total assets, with a correlation coefficient of 0.82 for our sample of firms over the 1976-1993 period during which real estate assets data are available in Compustat.

We obtain the headquarter locations of suppliers at the county level from Compustat, and house prices of the county where the suppliers' headquarters are located from the Federal Housing Finance Agency House Price (HP) Index.[4] We obtain similar results when we use Metropolitan Statistical Areas (MSAs) as regions and house prices at the MSA level. Since a firm's real estate assets are not always located in the same county as their headquarters, our proxy of the exposure to real estate shocks is prone to measurement error, which is likely to bias our results against finding any effect on a firm's sales. Campello, Connolly, Kankanhalli, and Steiner (2019) compute the market value of corporate real estate assets using commercial real estate transaction data including the geographical location of a firm's real estate assets. They find that the average firm has $100 million (6% of real estate assets) in market value at locations outside the region of their headquarters, and that the market value of real estate assets based on the headquarters and the actual locations of these assets display a high degree of correlation.

At the cost of a significant reduction in the sample size, and sample selection towards older firms that were active in 1993, in robustness tests we proxy for a supplier's exposure to the local real estate market in year t using alternative measures. A first measure is the ratio of PPE to total assets in year t multiplied by the average ratio of book value of real estate assets to the PPE of the firm during 1976-1993 (the book value of real estate assets is defined as PPE net of machinery, equipment, and leases). A second measure is the market value of real estate assets in 1993 multiplied by the change in the HP index from 1993 to a given year following Chaney, Sraer, and Thesmar (2012). The market value of real estate assets in 1993 is obtained by inflating the historical cost of a firm's real estate assets from the year of acquisition using the HP index. The average age of a firm's real estate assets in 1993 is given by the value of accumulated depreciation divided by the historical cost multiplied by a depreciable life of 40 years. A third measure is the market value of commercial real estate based on the geographical location of the

[4] A firm's financial information is reported for fiscal years, while house price data are reported for calendar years. To account for the increase in house prices during the firm's fiscal year, we proportionally adjust the house prices using information from two consecutive years for firms whose fiscal year does not end in December.

firm's real estate assets. Following Campello, Connolly, Kankanhalli, and Steiner (2019), we use commercial real estate transaction data from Real Capital Analytics to estimate the market value of corporate real estate assets.[5]

B. Summary Statistics

Panel A of Table I contains a year-by-year description of our sample. Our sample consists of 15,214 supplier-client-year observations for 2,229 suppliers and 485 clients over 2000-2015, with an average of slightly less than 1,000 observations per year. Sales to clients in our sample account, on average, for 36.7% of the total sales of sample firms. Panel A also shows that the coefficient of our variable of interest is estimated using the variation in real estate shocks of slightly more than five suppliers per client each year on average. There is also a large variation in real estate asset prices across the sample years. On average, the real estate asset prices in the counties where the suppliers are located increase by 4% per year, with a minimum corresponding to a decrease of 6.7% in 2009, and maximum corresponding to an increase of 12.9% in 2005. Thus, the fraction of suppliers located in counties with negative price changes varies from virtually zero in 2000-2005 to 96.1% in 2010, with a large degree of variation across years.

Panel B of Table I contains the summary statistics of the main variables. Panel B presents the summary statistics for the suppliers. The average book (market) leverage corresponds to 24.2% (20.8%) of total assets; the median values are about 7 percentage points lower, suggesting a skewed distribution with a few highly levered firms. There is a 4% average house price increase in counties in which the suppliers are located; however, 29.1% of all the observations correspond to firm-years with negative changes in local house prices.

We find that the average value of our main variable for real estate assets (*RE*), which corresponds to the ratio of PPE to total assets, is 23%, although this is highly variable across firms. This measure is highly correlated with the ratio of real estate assets to total assets over 1976-1993, the period in which data on real estate assets are available. However, this variable is

[5] We thank Eva Steiner for sharing the market value of commercial real estate data. For consistency with the analysis in Campello, Connolly, Kankanhalli, and Steiner (2019), we winsorize this variable at the 5% level.

likely overestimating the true ratio of real estate assets to total assets, leading to measurement error that could lead to an attenuation bias in our estimations. Indeed, real estate assets accounts on average (median) for 66.4% (81.1%) of PPE in 1976-1993.

Panel C of Table I shows that the clients in our sample are larger than their suppliers. This is due to regulation SFAS 14, which only requires disclose of the names of clients that account for at least 10% of the suppliers' total sales. These clients are also more levered than their suppliers; they hold more real estate assets and less cash. These clients are also less profitable than their suppliers, as indicated by a lower average *Tobin's q*. However, clients and suppliers are similarly exposed to changes in local house prices.

C. Methodology

Our identification strategy relies on analyzing whether clients reduce their purchases from suppliers that are more affected by a real estate shock than otherwise similar suppliers that are less affected by the shock. To investigate this hypothesis, we use a triple differences estimator:

$$\Delta \ln(Purchases)_{ijt} = \beta(\Delta HP < 0)_{it} High\ RE_{i,t-1} High\ Leverage_{i,t-1}$$

$$+\gamma X_{it} + \delta_{jt} + \varepsilon_{ijt}, \quad (1)$$

where i denotes suppliers and j denotes clients. The dependent variable measures the percentage change in the client's purchases from each supplier and is our main measure of economic distress. $(\Delta HP < 0)_{it}$ is a dummy variable that takes a value of one if the house price index (*HP*) in the county where the supplier i is located drops between year *t*–1 and year *t*, and zero otherwise. $High\ RE_{i,t-1}$ is a dummy variable that takes a value of one if the supplier *i* ratio of PPE to total assets is above the 75th percentile of the distribution. $High\ Leverage_{i,t-1}$ is a dummy variable that takes a value of one if the ratio of total debt to total assets (book leverage) is above the median of the distribution and is our main measure of financial constraints. X_{it} is a vector of supplier controls and δ_{jt} is client-by-year fixed effects.

Our coefficient of interest is the DDD coefficient (or triple interaction term) β. This coefficient estimates whether the difference between the response of the ex-ante highly levered treated firms relative to control firms, and the response of the low leverage treated firms relative to control firms is significant following a real estate shock. A negative coefficient would indicate that clients reduce their purchases from suppliers when they appear to be more affected by real estate shocks (i.e., highly levered firms with large real estate assets) and would support our main hypothesis that clients typically reduce more their exposure to suppliers in financial distress.[6]

Our client-supplier data allow us to include client-by-year fixed effects in regression equation (1), which ensures that identification comes from the variation, within the same year, of shocks to real estate across the suppliers of a given client. The client-by-time fixed effects absorbs all unobserved heterogeneity at the client level in a given period. Thus, concerns that our results are driven by changes in demand that coincide with a decline in local house prices are mitigated. The estimated difference in sales can be plausibly attributed to supply-side factors (i.e., differences in the financial distress of suppliers).

In all regressions, we also estimate coefficients for the variables $(\Delta HP < 0)_{it}$, $RE_{i,t-1}$, and $High\,Leverage_{i,t-1}$, as well as their interaction terms. Additionally, in some regressions we control for a set of supplier and client-supplier relationship characteristics that could affect their sales and be correlated with financial distress such as firm size (*Assets*), *Tobin's q*, cash to assets ratio (*Cash*), and house price index (*HP*). The Appendix provides variable definitions and data sources. We cluster the standard errors at the supplier level as it corresponds to the variation we explore in the main explanatory variable.

II. Results

A. Main Results

Table II presents the results of estimating our main regression in equation (1). The results in column (1) show that the coefficient of the DDD variable is negative and statistically significant.

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[6] An alternative interpretation for a negative coefficient, which is also consistent with a negative economic cost of financial distress, is that sale prices decrease more for distressed firms.

The effect of financial distress on a supplier's sales is also economically significant. The reduction in sales of the high leverage treated firms relative to control firms is 10.4% greater than the change in sales of low leverage treated firms relative to control firms when there is a drop in county-level house prices. The reduction in sales of about 10% implies that the average indirect costs of financial distress would be about 18% of firm value if we assume a price-to-sales ratio of 1.18 (the median in our sample). This estimate of the indirect costs of financial distress (as opposed to direct costs associated with bankruptcy) may be driven by a firm's impaired ability to conduct business when it is in financial distress. In fact, financial distress may affect a firm's product sales due to reputational concerns.

Column (2) presents the estimates of a regression where we control for the level of house prices in the county (*HP*). House prices in the county where the supplier has a presence could affect their sales and be correlated with financial distress. We find, however, that the coefficient of the DDD variable remains unchanged. The regression for the results in column (3) includes controls for the fundamentals of the supplier. We find that the estimate for the coefficient of the DDD variable is slightly lower but remains statistically and economically significant at -9.2%.

In columns (4)-(6), we present estimates of regressions in which we substitute the client-by-year fixed effects with supplier industry-by-client-by-year fixed effects. In this way, we can compare suppliers that operate in the same industry (two-digit SIC codes) but have different levels of financial distress and sales to the same client in the same year. This approach allows us to further mitigate the concern that our results may be driven by a demand shock, or other specific industry shock. The estimates of the coefficients of the DDD variable are 11.9% to 13.6% and remain statistically significant. These findings suggest that different exposures to county-level real estate shocks across suppliers and industries are unlikely to explain our results.

B. Alternative Measures of Real Estate Assets

In this subsection, we consider alternative measures for the suppliers' real estate assets. We estimate the real estate holdings of the firm as a product of the ratio of PPE to total assets in year *t* by the firm-level average ratio of real estate assets to PPE during the period 1976-1993 (*RE Adjusted*). The sample for these estimations is reduced by more than a half relative to our baseline estimation, as we impose the restriction that the firm was active in 1993. The sample is also selected towards older firms, which are likely to be less financially constrained (Hadlock and Pierce (2010)). In columns (1)-(3) of Panel A of Table 3, the coefficients of the DDD variable are negative and of similar magnitude to those in Table II; however, the coefficients are not statistically significant. The coefficients become statistically significant and economically stronger in columns (4)-(6) when we include the supplier industry-by-client-by-year fixed effects. These coefficients suggest that a supplier with high exposure to county-level housing shocks suffers a 22.9% to 28.1% stronger reduction in sales when there is a drop in house prices in the county where it is located, relative to another supplier in the same industry with low exposure to these real estate shocks.

In Panel B of Table III, our measure of real estate assets follows Chaney, Sraer, and Thesmar (2012) and is based on the market value of real estate in 1993 updated to year *t*, scaled by total assets, using the HP index (*Market RE*). Since the market prices of a firm's real estate assets are valued at historical cost, to calculate their value in 1993 we additionally require the availability of county-level house prices during the year of acquisition of the real estate asset. This imposes an additional constraint on the sample size because house prices are not observed before 1976. In fact, the sample size shrinks to about 10% of the sample of our baseline estimates in Table II. The coefficients of the DDD variable in Panel B of Table III are between -0.074 and -0.148, which are in line with our previous point estimates in Table II. The coefficients are statistically significant at the 10% level in columns (4) and (5), and economically stronger than in our baseline estimates using similar specifications.

We next examine real estate exposure using commercial real estate data (Campello, Connolly, Kankanhalli, and Steiner (2019)), as opposed to residential housing, obtained from Real Capital Analytics. This measure is based on transaction-level information and is calculated using the actual geographical location of the firm's real estate assets. These data are available between 2000 and 2015 for a subsample of our firms. We assume that the exposure of a firm with respect to commercial real estate prices is high if the market value of commercial real estate holdings scaled by PPE (*Commercial RE*) is above the 50th percentile of its distribution. We find that the DDD estimated coefficients in Panel C of Table 3 are between -0.054 and -0.124, which are in line with our previous estimates. The coefficients are statistically significant at the 10% level except in columns (3) and (6).

Table IA.1 in the Internet Appendix shows the results using an alternative measure of real estate assets. To compute the value of real estate assets when this item is not available in Compustat (post 1993), we take the product of the PPE to total assets ratio in year *t* by the industry average real estate assets to PPE ratio during 1976-1993. We find that the estimated coefficients of the DDD variable are -11% to -15% when we include client-by-year fixed effects in the regression and -13% to -17% when we include supplier industry-by-client-by-year fixed effects.

Overall, our results in this subsection are robust to using alternative measures of real estate assets. The coefficients are of similar magnitude to those in the baseline estimation in Table II but are estimated with less precision in some cases due to the smaller sample size.

C. Supplier-Client Location

Clients and suppliers may be located close to each other (Ellison, Glaeser, and Kerr (2010)). In particular, clients and suppliers may be located in the same county. Thus, local real estate shocks may affect the local demand for materials and therefore provide some explanatory power for why we observe a decrease in the sales of a supplier’s products or services. Our identification strategy addresses this concern by exploring within client-year variation. To further address this concern, we include supplier county-by-year fixed effects in the regressions to capture the source of time-varying unobserved county-level heterogeneity, such as a local economic shock. Panel A of Table IV presents the estimates. We find that the coefficient of the DDD variable is negative and significant. The magnitude of the effect is similar to that in Table II at about -12% to -15%

when client-by-year fixed effects are included in the regression and -15% to -17% when supplier industry-by-client-by-year fixed effects are included.

In an alternative approach, in Panel B of Table IV we presents regression results for the sub-samples of client-supplier pairs in which the geographic distance between supplier and client is below the median (low distance sample in columns (1), (3), and (5)) and above the median (high distance sample in columns (2), (4), (6)). We find that the coefficient of the DDD variable is negative but not statistically significant for client-suppliers located closer to each other (low distance sample). In contrast, the triple interaction coefficient is negative and statistically significant in the sample of client-suppliers located further away from each other (high distance sample). We conclude that clients are more likely to reduce purchases from suppliers in financial distress when the suppliers are geographically distant. This may be explained by information asymmetry between clients and suppliers, as clients may be less informed about suppliers that are further away. Thus, clients may want to reduce their exposure to financially distressed suppliers ahead of a potential disruption in production and/or liquidation. In addition, distant suppliers are less likely to be part of a local production network. Therefore, their clients are more likely to have a transactional relationship with them than a close relationship; their switching costs will likely be lower as well.

These findings also suggest that our main estimates are not contaminated by local economic shocks that may be correlated with real estate shocks. Our baseline results are mostly driven by the high distance sample for which local economic shocks for clients and suppliers are less likely to be correlated.

D. Alternative Measures of Financial Constraints

Our main measure of financial constraints is book leverage. In this subsection, we consider alternative measures of financial constraints. We use market leverage, the ratio of total debt to the market value of assets, to construct a dummy variable (*High Leverage*) that takes the value of one if market leverage is above the median of the distribution. The estimates in Panel A of Table

V show that the coefficients for *High Leverage* × *High RE* × Δ*HP*<0 are negative and significant. The magnitudes in Panel A of Table V are similar to those in Table II at about -10% to -11% in the regressions including client-by-year fixed effects (columns (1)-(3)) and slightly stronger at -14% to -16% in the regressions that include supplier industry-by-client-by-year fixed effects (columns (4)-(6)).

We also consider measures of financial constraints that do not rely exclusively on leverage. We consider the Kaplan-Zingales (KZ) index as a summary measure of financial constraints (Kaplan and Zingales (1997)). We classify supplier firms as *High KZ* (i.e., high financial constraints) if they have a KZ index above the median. Panel B of Table V shows that the coefficients for *High KZ* × *High RE* × Δ*HP*<0 are negative and significant when we replace the *High Leverage* dummy variable with the *High KZ* dummy variable. The magnitudes in Panel B of Table V are remarkably similar to those in Table II at about -10% to -11% when client-by-year fixed effects are included in the regression (columns (1)-(3)) and -12% to -13% when supplier industry-by-client-by-year fixed effects are included (columns (4)-(6)).

Our financial constraints measures so far rely on balance sheet information. We also consider a market-based measure of financial constraints. We use the distance to default measure, which is based on the Merton's (1974) bond pricing model. We estimate this measure following the approach proposed by Bharath and Shumway (2008). We classify suppliers as *Low DD* if they have a distance to default below the median, which corresponds to suppliers with high financial constraints. In Panel C of Table V, we find that coefficients for *Low DD* × *High RE* × Δ*HP*<0 are negative and significant. The magnitudes are similar to our baseline estimates at about -8% to -10% when client-by-year fixed effects are included in the regression (columns (1)-(3)) and -13% to -14% with supplier industry-by-client-by-year fixed effects (columns (4)-(6)) are included.[7]

In the regressions up to this point, we include dummy variables to measure financial

[7] We also use the expected default frequency (EDF) as a measure of financial constraints. EDF is calculated based on the distance to default measure, and we assume a normal distribution following Bharath and Shumway (2008). Table IA.2 in the Internet Appendix shows the results. The estimates of the DDD variable are negative and economically significant but imprecisely estimated.

constraints. We also estimate regressions that include a continuous leverage variable. The results in Panel A of Table VI show that the coefficients for the DDD variable are negative and statistically significant. The coefficient in column (1) is -0.260, which implies that a one standard deviation increase in leverage (0.288) is associated with a 7.5% decrease in sales for suppliers with a high exposure to county-level real estate shocks versus suppliers with low exposure to these shocks when there is a decline in local house prices.

Financial distress could also be severe if the supplier relies more on short-term debt financing (i.e., financing of less than one year), as opposed to long-term debt. Panel B of Table VI shows that the effect on supplier sales is also significant when we consider the ratio of short-term debt to total assets as our main measure of financial constraints. The coefficient of the DDD variable in column (1) is -0.582 and statistically significant, which implies that a one standard deviation increase in short-term debt (0.121) is associated with an additional 7% reduction in sales for suppliers with a high exposure to county-level housing real estate shocks versus suppliers with low exposure to these shocks when there is a decline in local house prices.

E. Placebo Tests

The change in real estate prices may be endogenous to the demand for a firm's products or services. A local economic shock could affect both real estate prices and the demand for a firm's products. Our identification strategy addresses this concern by including client-by-year fixed effects, which implies that we are exclusively relying on variation across suppliers that are affected differently by real estate shocks due to different levels of real estate assets and leverage. Thus, changes in a client's purchases due to a differential impact of local real estate shocks and/or economic shocks is unlikely to explain our findings as we perform a comparison across the suppliers of the same client in a given year. In addition, clients are not necessarily located in the same county and therefore may not be affected simultaneously by local real estate shocks.

To further validate our identification strategy, we estimate placebo regressions using the specification used to generate the results in column (1) of Table II. We estimate the DDD variable, *High Leverage* × *High RE* × Δ*HP*<0, in regressions in which we fix the real estate shock at time 0, and vary the dependent variable over a period between -3 and +3 years. Our identification strategy also assumes that the response of demand for a firm's products or services would have been the same for firms with different levels of leverage in the absence of the real estate shock. To validate this parallel trends assumption, we evaluate whether the trends in demand for firm's products or services for firms with high and low leverage are the same before the real estate shock.

Figure 1 shows the coefficients of the DDD variable and their 90% confidence intervals. We find no evidence of preexisting differential trends in sales between treated and control firms. Indeed, the estimated coefficient is lower than -0.050 and statistically insignificant from year -3 to year -1. The coefficient at time 0 is -0.104, as shown in Table II, and the coefficient at year +1 is also negative and significant at -0.084. The effect does not persist beyond two years of the shock as the coefficients for years 2 and 3 are not statistically significant.

Another issue is that there may be omitted factors that are correlated with both the firm's decision to own real estate and the demand for its products. A firm may be simultaneously more likely to own real estate assets and be more sensitive to local economic conditions. To address this issue, we control for the interaction of initial firm characteristics and real estate prices using the *HP* level. If these controls make the firm more likely to own real estate and more sensitive to changes in real estate prices, we are better able to identify the collateral channel when we control for the interaction between these controls and the contemporaneous real estate prices. Table IA.3 in the Internet Appendix shows that the DDD variable, *High Leverage* × *High RE* × Δ*HP*<0, estimated in this way are similar to those in Table II. Thus, the differential response to real estate prices across suppliers with different levels of real estate assets can be plausibly attributed to the collateral channel.

F. Extensive Margin

Our baseline results in Table II are determined under the assumption that clients and suppliers maintain their relationship during the year of the real estate shock; otherwise these transactions would not be observed in the data. Therefore, our baseline results are on the intensive margin. We also estimate an extensive margin regression. The dependent variable is a dummy that takes a value of one if we observe transactions in year t–1 but not in year t. We estimate the coefficients of the DDD variable, *High Leverage* × *High RE* × Δ*HP*<0, using a linear probability model, and present the results in Table VII. The coefficients are between 0.054 and 0.097 and statistically significant in four out of six regressions. This suggests that clients stop buying large amounts from a supplier when the supplier experiences a real estate shock. The coefficients indicate that the probability of losing a client is about 5 to 10 percentage points higher for a supplier with high exposure to real estate shocks versus a supplier with high exposure to real estate shocks after a shock.

Overall, the results are consistent with a significant decrease in sales for suppliers in financial distress due to real estate shocks, which can result in the decline or loss of some client-supplier relationships. A caveat is that when we do not observe such transactions, it may not necessarily indicate a client stops buying from a supplier, but instead that this client's purchases are not above the 10% threshold imposed for reporting purposes.

G. Financial Crisis

Financial distress is more likely to happen in economic downturns. Thus, the mechanism that we explore is more likely when there are large negative changes in real estate prices such as those that took place during the 2007-2009 financial crisis. We estimate our baseline regression in Table II for the 2007-2009 period and present the results in Panel A of Table VIII. We find that the coefficients of the DDD variable are negative and significant. The magnitude of the coefficients is larger than in the baseline regression at about -22% to -23% with client-by-year fixed effects and -28 to -29% with supplier industry-by-client-by-year fixed effects.

Real estate markets performed poorly from 2007 until 2011 as the average change in house prices is significantly negative and more than 50% of the counties recorded reductions in house prices. Panel B of Table VIII presents the estimates of regressions using the 2007-2011 period. We find that the estimates of the DDD variable are slightly lower than those in Panel A of Table VIII.

H. Heterogeneity

In this subsection, we examine the heterogeneity of the relation between financial distress and economic distress. We test several empirical predictions.

First, we test the prediction that the negative effect of a supplier's financial distress on a client's purchases should be more pronounced when the supplier has a lower market share in the industry (calculated at the three-digit SIC code level). Suppliers with high market share are likely to have more market power and bargaining power, which could allow them to impose higher switching costs to their clients (Klemperer (1987)). Therefore, suppliers with lower market share might suffer a more pronounced drop in a client's purchases relative to suppliers with higher market share. Columns (1) and (2) of Table IX present the results of regressions with supplier industry-by-client-by-year fixed effects to estimate the regression coefficients separately for groups of suppliers with lower and higher than median values, respectively, in the distribution of the yearly market share. We find that the negative effect of financial distress is only statistically and economically significant in the group of suppliers with low market share, which are likely to have less market power. The decrease in sales is much less pronounced and statistically insignificant in the group of suppliers with high market share.

Second, we test the prediction that the negative effect of financial distress on a client's purchases is more pronounced when the supplier operates in a more competitive industry. In more competitive industries, firms might be more sensitive to financial distress. Clients might have a higher expectation that suppliers will run out of business and therefore reduce their exposure to these suppliers. Moreover, financially distressed suppliers operating in competitive environments have a higher potential for compromising quality and/or service provision (Maksimovic and Titman (1991), Hanka (1998), Matsa (2011)). We consider three proxies of competition: number of firms in the three-digit SIC industry, 1 – Lerner index (where the Lerner index is the median net margin in each industry and year), and 1 – net margin at the firm level. Columns (3)-(8) in Table IX present the estimates for groups of low and high competition firms according to the median value of the distribution of each measure. We consistently find that the negative effect of financial distress is more pronounced in the group of suppliers that operate in more competitive industries than in less competitive industries, i.e., high number of firms, high 1 – Lerner index, and high 1 – net margin. The coefficient of the triple interaction term ranges from -0.16 to -0.25 in the high competition groups and is always statistically and economically significant. The coefficient is economically smaller and not statistically significant in the low competition groups.

Third, we test the prediction that the negative effect of financial distress on supplier's sales should be more pronounced when the supplier produces a more specialized product. We construct three measures of supplier's product specificity: the ratio of R&D expenditures to assets; the ratio of intangible assets to total assets to capture the importance of relationship-specific investment and differentiated product; and R&D output as measured by patent counts to capture restrictions on alternative sources of inputs. Table X presents the results. Columns (1) and (2) present results for the sample firms split into low and high R&D firms according to the median value of its distribution. We find that the coefficient of the DDD variable is -0.26 and statistically significant in the group of suppliers with low R&D expenditures and not statistically significant in the group of suppliers with high R&D expenditures. Columns (3) and (4) present results for the sample split into suppliers with no patents and suppliers with patents filed in a given year. We find that the negative effect of financial distress is significant at -0.18 in the group of suppliers with no patents, while the effect is insignificant in the group of suppliers with patents. Columns (5) and (6) present the results for the group of suppliers with low and high intangibles split at the median. We find that the effect of financial distress is only significant in the group with low intangibles at -0.39. These findings using R&D expenditures, patent counts, and intangibles indicate that the effect of financial distress is more pronounced when the supplier produces a less specific product, which is easier to substitute with another supplier. In addition, the results are consistent with the notion that the negative effect for suppliers of specific goods is mitigated by the fact that clients may build up inventory of the supplier's goods for precautionary reasons.

Fourth, we test the prediction that the negative effect of financial distress is more pronounced if the supplier sells a durable good, or if it operates in the manufacturing industry. Durable goods and manufactured goods typically require post-purchase client service and clients might be concerned that the supplier will get liquidated and not be able to provide this service. In addition, if a financially constrained supplier compromises the quality its product, this might have a more serious and longer impact for durable goods. Table XI presents the results. Columns (1) and (2) present the results for the group of suppliers that produce durable and non-durable goods based on the Fama-French industry classification. Consistent with our predictions, we find that the coefficient of the DDD variable, *High Leverage* × *High RE* × $\Delta HP<0$, is negative and significant in the case of durable goods and not statistically significant in the case of non-durable goods. Columns (3) and (4) present the results for the group of suppliers in the non-manufacturing sector and manufacturing sector based the Fama-French industry classification. We find that the negative effect of financial distress is more pronounced for suppliers in the manufacturing sector at -0.50, while the effect is -0.11 in the non-manufacturing sector.

Last, we test the prediction that the negative effect of financial distress on a client's purchases is more pronounced when client and supplier have a stronger relationship. If there is a stronger relationship and dependence, it is more likely that a client will attempt to reduce its exposure to avoid a potential supply chain disruption. We proxy for the importance of the supplier (to the client) using the ratio of sales between the client and supplier divided by the cost of goods sold of the client (supplier weight). Table XII presents the results. Columns (1) and (2) present results for the sample split into low and high supplier weight according to the yearly median of the distribution. We find that the negative effect of financial distress is more pronounced when the supplier weight is higher (i.e, the client is more dependent on a particular supplier).

We then further split the samples of low and high supplier weight into client-supplier pairs in which the geographic distance between supplier and client is below the median (columns (3) and (5)) and above the median (columns (4) and (6)). Column (4) shows that the negative effect of financial distress when the client is more dependent on one supplier is concentrated in the sample of client-suppliers located further away from each other (high distance sample). We conclude that clients want to hedge against a potential disruption in their supply chain by reducing their dependence on financially distressed suppliers. They more likely to switch suppliers when switching costs are low as proxied by geographic distance.

I. Robustness

In this subsection, we discuss several robustness checks of our primary findings. The results are in the Internet Appendix.

A first concern is whether the segment sales data are representative of the total sales of the supplier firm. In particular, firms are only required to disclose the identity of any client representing more than 10% of the total sales. During our 2000-2015 sample period, the sum of reported sales represents on average of 37% of total sales (the median is 30%). We run our regressions with the sample of suppliers for which the sum of reported sales represents at least 30% (the median). Table IA.4 reports the results, which are consistent with the results in Table II but more imprecisely estimated. The magnitudes of the coefficients of the DDD variable are similar at about -8% to -13% with client-by-year fixed effects and -15% to -20% with supplier industry-by-client-by-year fixed effects.

In our main tests, we use the headquarters location as a proxy for the location of a firm's real estate assets. Specifically, we use the HP index of the county where the suppliers' headquarters are located. This assumes that headquarters and other facilities tend to be clustered in the same county and that the headquarters represent an important fraction of the firms' real estate assets. This assumption introduces measurement error, which generates attenuation bias in our estimates. To check the robustness of the results to this assumption, we estimate the regressions using the state-level weighted HP index with weights given by the value of real estate assets located in each state (Garcia and Norli (2012)). The sample in this case is smaller. Table IA.5, Panel A, reports the results. The results are consistent with those in Table II as the coefficient of the DDD variable is negative and significant. The magnitude of the coefficient is -20% to -21% with client-by-year fixed effects and -18% to -22% with supplier industry-by-client-by-year fixed effects. This is consistent with the notion that our baseline estimates suffer from attenuation bias. In Panel B of Table IA.5, we exclude firms whose Herfindahl-Hirschman Index (HHI) of real estate assets across states is below the median. Thus, we focus on firms whose real estate is more concentrated in a given state. The results are also consistent with our baseline estimates with coefficients between -0.24 and -0.48. In Table IA.6, we restrict the sample to suppliers that operate in a single business segment as their real estate assets are more likely to be located in the county of the headquarters. The estimated coefficients are -16% to -17% with client-by-year fixed effects and -22% to -24% with supplier industry-by-client-by-year fixed effects.

In our main tests, we use county-level house prices. As an alternative, we use MSA-level prices. Table IA.7 reports the results. We find that the magnitude of the coefficient of the DDD variable is larger than in Table II. The coefficients are -14% to -15% with client-by-year fixed effects and -21% to -23% with supplier industry-by-client-by-year fixed effects.

Table IA.8 reports the results for the subsample of small suppliers located in large counties. In this test, we address the potential concern of reverse causality (i.e., that the financial distress of a supplier might itself cause the local real estate shock. By restricting the sample to small suppliers (below the 95th percentile of total assets) in large geographical areas (above the 95th percentile of county population), we reduce the chances of reverse causality. We find that the coefficients for this subsample are -14% to -15% with client-by-year fixed effects and -17% to -19% with supplier industry-by-client-by-year fixed effects.

Table IA.9 reports the results when we exclude the sample industries with high exposure to real estate shocks based on the RE variable. In Panels A-E, we exclude energy, utilities, telecoms, shops, and manufacturing (Fama-French industry classification), respectively. The results are consistent with our baseline results in Table II with point estimates between -6.3% and -14.1%.

Our baseline results include real estate assets reported as a firm's fixed assets in the balance sheet. However, some of these assets may not be owned, they may be leased. If this is the case, these assets cannot be used as collateral. As robustness check, we exclude leases from our definition of real estate assets. Table IA.10 shows the results. Consistent with the notion that leased assets cannot be used as collateral, the estimated coefficients are larger. The estimated coefficients of the DDD variable are -11% to -13% with client-by-year fixed effects and -14% to -16% with supplier industry-by-client-by-year fixed effects.

In our baseline results, both the client and supplier might be affected by a real estate shock. To isolate the shock at the supplier level, we restrict the sample to clients that are not affected by real estate shocks and to pairs in which the client and supplier operate in different states. Table IA.11 shows the results. Our point estimates are larger in magnitude with the coefficients of the DDD variable between -9% and -22%, but are not statistically significant due to a smaller sample size and the lower variation across suppliers for the same client-year.

We assume that there is a negative real estate shock if the house prices decrease (i.e., if ΔHP is negative). As an alternative, we use a more restrictive definition of negative real estate shock (-3.3%, which corresponds to the first decile of the distribution of ΔHP). Table IA.12 shows that the estimated coefficients of the DDD variable are -9% to -14%.

In our baseline tests, we measure the real estate shock contemporaneously to the change in purchases. We also consider the case when the real estate shock is measured at year $t-1$ instead of year t. The results in Table IA.13 are consistent with those reported in Table II. Indeed, the coefficients of the DDD variable are between -11% and -13% and statistically significant.

III. Conclusion

We estimate the indirect costs of financial distress using client-supplier pair data and real estate shocks for the 2000-2015 period. We identify the effects of financial distress by exploiting cross-supplier variation in real estate assets and leverage, and the timing of real estate shocks. We find that clients reduce their reliance on suppliers that are in financial distress triggered by a county-level real estate shock: for the same client buying from different suppliers, its purchases from financially distressed suppliers decline by an additional 10% following a reduction in real estate prices. In addition, our results show that this effect is more pronounced across suppliers operating in the same industry, which suggests that firms switch from financially distressed suppliers to non-financially distressed ones within the same industry. In fact, when we restrict the analysis to within supplier industry variation, we find that sales fall by about 14% more for suppliers with high exposure to real estate shocks. Our results are also more pronounced for more geographically distant suppliers, which suggest that firms reduce their purchases more from financially distressed suppliers when the costs of switching suppliers are low and information asymmetries are high. While we explore within client-year variation across suppliers that control for demand-side factors, this finding further reduces concerns that our results are driven by shocks to local demand in the geographical area of the client.

Our results show that the economic costs of financial distress are more pronounced during the 2007-2009 financial crisis. The decrease in sales for financially distressed suppliers is about 22% during the financial crisis. The economic costs of financial distress are also more pronounced for manufacturing and durable goods industries, less specific goods, and more competitive industries.

The costs of financial distress are an important deviation from the Modigliani and Miller (1958) framework with no frictions. We provide evidence that the economic costs of financial distress are sizable and thus should be an important consideration of capital structure decisions. Our results suggest that financial shocks may be amplified by the economic costs of financial distress due to real estate shocks through the balance sheet channel.

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Table I: Sample Description and Summary Statistics

Panel A presents the number of observations (supplier-client pairs), number of suppliers, number of clients, average number of suppliers per client, and average fraction of total sales of the supplier included in the sample per year. Panel A also presents the average percentage change (ΔHP) in the house price index (HP) of the county where the supplier is located and the fraction of observations with negative ΔHP. Panels B and C present mean, median, standard deviation, 5th percentile, 95th percentile, and number of observations for each supplier and client variable, respectively. Variable definitions are in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period.

Panel A: Sample Description by Year

Year	Number of Observations	Number of Suppliers	Number of Clients	Average Number of Suppliers per Client	Average Supplier Sales Coverage	Average ΔHP	Fraction ΔHP<0
2000	765	548	145	5.28	0.378	0.114	0.004
2001	1,018	690	181	5.62	0.382	0.087	0.000
2002	1,057	695	196	5.39	0.381	0.067	0.000
2003	1,123	760	198	5.67	0.359	0.053	0.001
2004	1,087	732	202	5.38	0.364	0.091	0.003
2005	1,029	696	196	5.25	0.374	0.129	0.000
2006	1,080	725	197	5.48	0.355	0.081	0.072
2007	1,007	702	186	5.41	0.358	0.011	0.450
2008	938	661	173	5.42	0.354	-0.053	0.794
2009	910	644	180	5.06	0.359	-0.067	0.852
2010	934	647	177	5.28	0.355	-0.036	0.961
2011	879	597	163	5.39	0.372	-0.029	0.936
2012	883	597	159	5.55	0.371	-0.003	0.533
2013	889	588	171	5.20	0.374	0.054	0.109
2014	853	549	170	5.02	0.368	0.084	0.022
2015	762	500	150	5.08	0.381	0.057	0.006
Total	15,214	2,229	485	5.35	0.367	0.040	0.291

Table I: continued

Panel B: Supplier Variables

	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	Number of Suppliers	Number of Observations
Δlog(Sales)	0.030	0.038	0.512	-0.809	0.834	10,331	15,214
Leverage	0.242	0.175	0.288	0.000	0.697	10,331	15,214
High Leverage	0.436	0.000	0.496	0.000	1.000	10,331	15,214
Market Leverage	0.208	0.121	0.242	0.000	0.742	9,411	13,987
Short-Term Leverage	0.045	0.006	0.121	0.000	0.211	10,331	15,214
KZ Index	-10.055	-1.571	32.129	-49.290	3.639	8,740	12,981
High KZ Index	0.398	0.000	0.490	0.000	1.000	8,740	12,981
HP	6.021	5.006	3.209	2.415	12.758	10,331	15,214
ΔHP	0.040	0.035	0.079	-0.083	0.175	10,331	15,214
ΔHP<0	0.291	0.000	0.454	0.000	1.000	10,331	15,214
RE	0.233	0.158	0.223	0.018	0.766	10,331	15,214
High RE	0.249	0.000	0.432	0.000	1.000	10,331	15,214
RE Adjusted	0.153	0.093	0.188	0.003	1.000	4,678	6,809
High RE Adjusted	0.144	0.000	0.351	0.000	1.000	4,678	6,809
Market RE	0.238	0.154	0.354	0.014	0.754	1,256	1,678
High Market RE	0.212	0.000	0.409	0.000	1.000	1,256	1,678
Commercial RE	0.799	0.499	0.847	0.000	3.056	1,107	1,480
High Commercial RE	0.524	1.000	0.500	0.000	1.000	1,107	1,480
Tobin's q	2.176	1.514	2.676	0.771	5.518	8,950	13,262
Cash	0.157	0.098	0.172	0.002	0.526	10,274	15,096
Assets (log)	5.872	5.837	1.999	2.692	9.150	10,331	15,214

Panel C: Client Variables

	Mean	Median	Standard Deviation	5th Percentile	95th Percentile	Number of Clients	Number of Observations
Δlog(Sales)	0.030	0.038	0.512	-0.809	0.834	2,844	15,214
Leverage	0.258	0.247	0.166	0.042	0.601	2,023	11,983
High Leverage	0.551	1.000	0.497	0.000	1.000	2,023	11,983
Market Leverage	0.260	0.185	0.228	0.017	0.838	1,872	11,558
HP	5.592	4.489	3.179	2.607	12.836	2,031	11,995
ΔHP	0.035	0.034	0.073	-0.074	0.155	2,031	11,995
ΔHP<0	0.295	0.000	0.456	0.000	1.000	2,031	11,995
RE	0.307	0.256	0.223	0.032	0.637	2,027	11,995
High RE	0.430	0.000	0.495	0.000	1.000	2,027	11,995
Tobin's q	1.767	1.497	1.052	0.928	3.682	1,562	9,398
Cash	0.074	0.055	0.065	0.006	0.196	2,008	11,724
Assets (log)	10.614	10.620	1.418	8.335	12.620	2,027	11,995

Table II: Baseline Results

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. *Tobin's q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.104**	-0.105**	-0.092*	-0.133**	-0.136**	-0.119*
	(0.025)	(0.025)	(0.065)	(0.032)	(0.029)	(0.072)
High Leverage	0.004	0.005	-0.004	-0.001	-0.001	-0.006
	(0.789)	(0.703)	(0.801)	(0.956)	(0.964)	(0.765)
High RE	-0.024	-0.019	-0.017	-0.055*	-0.051*	-0.041
	(0.249)	(0.358)	(0.408)	(0.062)	(0.085)	(0.176)
ΔHP<0	-0.009	-0.020	-0.015	-0.011	-0.022	-0.019
	(0.709)	(0.396)	(0.543)	(0.736)	(0.488)	(0.588)
High Leverage × High RE	0.030	0.029	0.028	0.050	0.051	0.050
	(0.244)	(0.263)	(0.293)	(0.145)	(0.140)	(0.174)
High Leverage × ΔHP<0	0.014	0.014	0.004	0.010	0.010	0.001
	(0.558)	(0.559)	(0.887)	(0.763)	(0.765)	(0.974)
High RE × ΔHP<0	0.067*	0.071*	0.058	0.093*	0.099*	0.100*
	(0.066)	(0.051)	(0.124)	(0.075)	(0.059)	(0.069)
HP		0.006***	0.004*		0.007***	0.006**
		(0.001)	(0.072)		(0.007)	(0.030)
Tobin's q			0.013***			0.022***
			(0.000)			(0.000)
Cash			-0.069			-0.093
			(0.131)			(0.150)
Assets (log)			0.013***			0.009*
			(0.000)			(0.055)
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,214	15,214	12,806	10,877	10,877	9,012
R-squared	0.286	0.286	0.294	0.353	0.354	0.366

Table III: Alternative Measures of Real Estate Assets

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. In Panel A, *High RE Adjusted* is a dummy variable that takes a value of one if *RE Adjusted* is above the 75th percentile, and zero otherwise. *RE Adjusted* is the product of the ratio of PPE to total assets by the average firm-level fraction of the PPE that corresponds to buildings between 1976 and 1993. In Panel B, *High Market RE* is a dummy variable that takes a value of one if *Market RE* is above the 50th percentile, and zero otherwise. *Market RE* is the product of the market value of real estate in 1993 by the change in the market value of real estate in the county where the firm is located between 1993 and the current year, scaled by total assets. In Panel C, *High Commercial RE* is a dummy variable taking the value of one if *Commercial RE* is above the 50th percentile, and zero otherwise. *Commercial RE* is the market value of commercial real estate based on transaction data and the true geographical location of the firms' real estate assets scaled by PPE. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Adjusted Real Estate

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE Adjusted × ΔHP<0	-0.092	-0.091	-0.081	-0.279***	-0.281***	-0.229**
	(0.286)	(0.289)	(0.351)	(0.006)	(0.006)	(0.023)
High Leverage	0.026	0.027	-0.001	0.002	0.003	-0.016
	(0.111)	(0.103)	(0.971)	(0.914)	(0.901)	(0.496)
High RE Adjusted	-0.021	-0.021	-0.024	-0.037	-0.037	-0.035
	(0.509)	(0.511)	(0.456)	(0.415)	(0.418)	(0.403)
ΔHP<0	0.013	0.006	0.012	0.018	0.013	0.025
	(0.611)	(0.828)	(0.658)	(0.625)	(0.721)	(0.525)
High Leverage × High RE Adjusted	0.009	0.008	0.015	0.100*	0.099*	0.100*
	(0.827)	(0.838)	(0.711)	(0.056)	(0.057)	(0.059)
High Leverage × ΔHP<0	-0.015	-0.017	-0.020	-0.011	-0.011	-0.022
	(0.589)	(0.541)	(0.496)	(0.758)	(0.752)	(0.567)
High RE Adjusted × ΔHP<0	0.115*	0.119*	0.112*	0.146*	0.149*	0.130
	(0.061)	(0.051)	(0.062)	(0.074)	(0.066)	(0.108)
HP		0.005*	0.003		0.003	0.001
		(0.064)	(0.351)		(0.473)	(0.805)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	6,809	6,809	6,082	4,496	4,496	3,993
R-squared	0.311	0.312	0.325	0.408	0.408	0.417

Table III: continued

Panel B: Market Value of Real Estate

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High Market RE × ΔHP<0	-0.126	-0.125	-0.074	-0.148*	-0.141*	-0.096
	(0.165)	(0.170)	(0.415)	(0.081)	(0.095)	(0.277)
High Leverage	-0.022	-0.021	-0.029	-0.099**	-0.098**	-0.095**
	(0.495)	(0.514)	(0.418)	(0.019)	(0.020)	(0.032)
High Market RE	-0.086*	-0.094**	-0.066	-0.141***	-0.147***	-0.126**
	(0.078)	(0.048)	(0.128)	(0.008)	(0.006)	(0.021)
ΔHP<0	-0.025	-0.024	-0.007	-0.034	-0.031	-0.011
	(0.584)	(0.612)	(0.895)	(0.397)	(0.441)	(0.780)
High Leverage x High Market RE	0.075	0.078	0.065	0.140**	0.141**	0.141**
	(0.194)	(0.165)	(0.244)	(0.033)	(0.031)	(0.037)
High Leverage × ΔHP<0	0.021	0.011	0.002	0.036	0.030	0.028
	(0.660)	(0.824)	(0.972)	(0.417)	(0.515)	(0.493)
High Market RE × ΔHP<0	0.095	0.092	0.016	0.139*	0.131*	0.037
	(0.147)	(0.156)	(0.783)	(0.060)	(0.065)	(0.546)
HP		0.012***	0.009**		0.006	0.005
		(0.007)	(0.031)		(0.313)	(0.268)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	1,678	1,678	1,426	943	943	816
R-squared	0.362	0.366	0.365	0.417	0.419	0.437

Panel C: Market Value of Commercial Real Estate

	(1)	(2)	(3)	(4)	(5)	(6)
High Lev. × High Commercial RE × ΔHP<0	-0.122*	-0.111*	-0.054	-0.124*	-0.114*	-0.123
	(0.052)	(0.082)	(0.428)	(0.073)	(0.099)	(0.126)
High Leverage	-0.012	-0.012	-0.006	-0.004	-0.012	-0.012
	(0.753)	(0.735)	(0.893)	(0.940)	(0.829)	(0.846)
High Commercial RE	-0.034	-0.035	-0.024	-0.040	-0.047	-0.033
	(0.335)	(0.298)	(0.481)	(0.400)	(0.260)	(0.454)
ΔHP<0	0.061	0.034	0.031	0.046	0.006	-0.001
	(0.176)	(0.448)	(0.548)	(0.344)	(0.897)	(0.992)
High Leverage x High Commercial RE	0.067	0.066	0.024	0.028	0.036	0.019
	(0.132)	(0.122)	(0.588)	(0.673)	(0.566)	(0.781)
High Leverage × ΔHP<0	0.013	0.008	-0.012	0.027	0.025	0.038
	(0.780)	(0.869)	(0.822)	(0.625)	(0.659)	(0.544)
High Commercial RE × ΔHP<0	0.094**	0.092**	0.079	0.148***	0.150***	0.162***
	(0.041)	(0.042)	(0.116)	(0.006)	(0.005)	(0.006)
HP		0.011***	0.009**		0.011**	0.009**
		(0.005)	(0.020)		(0.011)	(0.013)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	1,480	1,480	1,253	950	950	824
R-squared	0.407	0.414	0.432	0.451	0.460	0.458

Table IV: Client-Supplier Location

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. In Panel B, the low and high distance groups consist of those supplier-client pairs in which the geographic distance between the supplier and client headquarters is below and above the median. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Supplier County-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.149**	-0.149**	-0.121*	-0.174**	-0.173**	-0.152
	(0.020)	(0.020)	(0.083)	(0.044)	(0.045)	(0.113)
High Leverage	-0.001	-0.001	-0.011	-0.013	-0.013	-0.019
	(0.942)	(0.936)	(0.552)	(0.595)	(0.601)	(0.514)
High RE	-0.034	-0.034	-0.053*	-0.081**	-0.081**	-0.091**
	(0.213)	(0.212)	(0.052)	(0.048)	(0.049)	(0.028)
ΔHP<0	-0.029	-0.028	-0.010	-0.073	-0.074	-0.064
	(0.507)	(0.531)	(0.829)	(0.190)	(0.187)	(0.285)
High Leverage × High RE	0.036	0.036	0.047	0.081*	0.081*	0.091*
	(0.277)	(0.275)	(0.179)	(0.086)	(0.088)	(0.074)
High Leverage × ΔHP<0	0.025	0.025	0.009	0.022	0.022	0.007
	(0.428)	(0.425)	(0.792)	(0.611)	(0.615)	(0.882)
High RE × ΔHP<0	0.069	0.069	0.089*	0.076	0.076	0.114
	(0.160)	(0.160)	(0.087)	(0.297)	(0.298)	(0.154)
HP		-0.008	-0.014		0.006	0.006
		(0.873)	(0.783)		(0.913)	(0.917)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Supplier County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,805	13,805	11,484	9,527	9,527	7,695
R-squared	0.411	0.411	0.435	0.508	0.508	0.533

Table IV: continued

Panel B: Sample Split Based on Client-Supplier Distance

	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.067	-0.315**	-0.067	-0.322**	-0.043	-0.331**
	(0.432)	(0.020)	(0.433)	(0.018)	(0.674)	(0.014)
High Leverage	-0.002	-0.042	-0.003	-0.040	0.007	-0.057*
	(0.930)	(0.146)	(0.923)	(0.161)	(0.813)	(0.056)
High RE	-0.039	-0.103*	-0.039	-0.097	-0.027	-0.104
	(0.312)	(0.091)	(0.320)	(0.106)	(0.504)	(0.112)
ΔHP<0	0.013	0.013	0.011	0.003	0.027	0.027
	(0.780)	(0.778)	(0.813)	(0.956)	(0.596)	(0.602)
High Leverage × High RE	0.011	0.127*	0.010	0.128*	0.013	0.149*
	(0.825)	(0.086)	(0.830)	(0.083)	(0.808)	(0.051)
High Leverage × ΔHP<0	-0.007	0.034	-0.007	0.032	-0.032	0.037
	(0.889)	(0.486)	(0.881)	(0.508)	(0.527)	(0.489)
High RE × ΔHP<0	0.062	0.184*	0.062	0.196*	0.050	0.188*
	(0.404)	(0.077)	(0.398)	(0.058)	(0.576)	(0.064)
HP			0.003	0.006	0.000	0.002
			(0.640)	(0.160)	(0.952)	(0.594)
Firm-Level Controls	No	No	No	No	Yes	Yes
Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,411	3,500	3,411	3,500	2,811	2,899
R-squared	0.415	0.386	0.415	0.386	0.410	0.398

Table V: Alternative Measures of Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. In Panel A, *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to the market value of assets is above the median, and zero otherwise. In Panel B, *High KZ* is a dummy variable that takes a value of one if the Kaplan-Zingales index is above the median, and zero otherwise. In Panel C, *High DD* is a dummy variable that takes a value of one if the distance to default is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market Leverage

	(1)	(2)	(3)	(4)	(5)	(6)
High Market Leverage × High RE × ΔHP<0	-0.104**	-0.105**	-0.106**	-0.158**	-0.160***	-0.136**
	(0.039)	(0.037)	(0.039)	(0.011)	(0.010)	(0.033)
High Market Leverage	-0.004	-0.002	-0.003	-0.014	-0.012	-0.004
	(0.785)	(0.876)	(0.856)	(0.489)	(0.537)	(0.859)
High RE	-0.006	-0.003	-0.005	-0.030	-0.025	-0.023
	(0.765)	(0.894)	(0.798)	(0.300)	(0.382)	(0.432)
ΔHP<0	-0.016	-0.023	-0.021	-0.024	-0.036	-0.023
	(0.499)	(0.310)	(0.396)	(0.451)	(0.264)	(0.503)
High Market Leverage × High RE	0.012	0.011	0.010	0.024	0.024	0.021
	(0.668)	(0.695)	(0.725)	(0.489)	(0.497)	(0.550)
High Market Leverage × ΔHP<0	0.027	0.028	0.023	0.028	0.030	0.015
	(0.267)	(0.245)	(0.389)	(0.378)	(0.342)	(0.664)
High RE × ΔHP<0	0.056	0.058	0.059	0.109**	0.113**	0.105**
	(0.145)	(0.129)	(0.124)	(0.032)	(0.027)	(0.049)
HP		0.004**	0.004*		0.007**	0.006**
		(0.035)	(0.071)		(0.020)	(0.032)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	13,750	13,750	12,806	9,660	9,660	9,012
R-squared	0.287	0.288	0.294	0.360	0.360	0.366

Table V: continued

Panel B: Kaplan-Zingales Index

	(1)	(2)	(3)	(4)	(5)	(6)
High KZ × High RE × ΔHP<0	-0.105*	-0.103*	-0.101*	-0.122*	-0.121*	-0.125*
	(0.051)	(0.054)	(0.058)	(0.074)	(0.079)	(0.064)
High KZ	-0.026	-0.025	-0.030*	-0.011	-0.010	-0.015
	(0.120)	(0.140)	(0.081)	(0.614)	(0.663)	(0.516)
High RE	0.006	0.009	0.000	-0.005	-0.001	-0.011
	(0.814)	(0.727)	(0.989)	(0.904)	(0.983)	(0.784)
ΔHP<0	-0.022	-0.028	-0.027	-0.016	-0.026	-0.025
	(0.350)	(0.242)	(0.266)	(0.634)	(0.426)	(0.452)
High KZ × High RE	0.006	0.005	0.014	-0.007	-0.007	0.005
	(0.841)	(0.864)	(0.646)	(0.870)	(0.873)	(0.911)
High KZ × ΔHP<0	0.061**	0.061**	0.058*	0.024	0.025	0.025
	(0.049)	(0.050)	(0.065)	(0.578)	(0.562)	(0.562)
High RE × ΔHP<0	0.060	0.060	0.056	0.104*	0.104*	0.107*
	(0.174)	(0.173)	(0.190)	(0.063)	(0.062)	(0.052)
HP		0.004	0.003		0.006**	0.006*
		(0.107)	(0.157)		(0.030)	(0.052)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	12,599	12,599	12,481	8,861	8,861	8,786
R-squared	0.290	0.290	0.296	0.362	0.363	0.368

Panel C: Distance to Default

	(1)	(2)	(3)	(4)	(5)	(6)
Low DD × High RE × ΔHP<0	-0.081	-0.082	-0.103*	-0.126*	-0.128*	-0.138**
	(0.126)	(0.123)	(0.057)	(0.059)	(0.056)	(0.046)
Low DD	-0.036**	-0.037**	-0.025	-0.008	-0.009	0.000
	(0.015)	(0.012)	(0.102)	(0.713)	(0.644)	(0.991)
High RE	0.020	0.023	0.012	-0.015	-0.011	-0.018
	(0.299)	(0.245)	(0.547)	(0.608)	(0.687)	(0.544)
ΔHP<0	-0.002	-0.009	-0.012	0.003	-0.007	-0.000
	(0.918)	(0.698)	(0.627)	(0.933)	(0.816)	(0.991)
Low DD × High RE	-0.030	-0.029	-0.021	-0.022	-0.021	-0.010
	(0.243)	(0.258)	(0.427)	(0.508)	(0.535)	(0.763)
Low DD × ΔHP<0	-0.003	-0.002	0.008	-0.002	0.000	0.013
	(0.904)	(0.935)	(0.767)	(0.952)	(0.996)	(0.730)
High RE × ΔHP<0	0.059	0.061	0.072*	0.106**	0.110**	0.110**
	(0.129)	(0.116)	(0.070)	(0.037)	(0.029)	(0.032)
HP		0.003*	0.003		0.005*	0.005
		(0.098)	(0.193)		(0.067)	(0.126)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	12,273	12,273	11,385	8,660	8,660	8,058
R-squared	0.297	0.298	0.304	0.368	0.368	0.372

Table VI: Continuous Measures of Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. In Panel A, *Leverage* is the ratio of total debt to total assets. In Panel B, *Short-Term Leverage* is the ratio of short-term debt to total assets. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Leverage

	(1)	(2)	(3)	(4)	(5)	(6)
Leverage × High RE × ΔHP<0	-0.260**	-0.259**	-0.222	-0.293*	-0.294*	-0.215
	(0.020)	(0.021)	(0.108)	(0.055)	(0.055)	(0.240)
Leverage	-0.026	-0.022	-0.065	-0.007	-0.003	-0.013
	(0.446)	(0.517)	(0.155)	(0.869)	(0.935)	(0.807)
High RE	-0.024	-0.018	-0.020	-0.064*	-0.059	-0.043
	(0.373)	(0.495)	(0.520)	(0.079)	(0.108)	(0.284)
ΔHP<0	-0.019	-0.030	-0.030	-0.011	-0.022	-0.020
	(0.411)	(0.204)	(0.249)	(0.740)	(0.503)	(0.588)
Leverage × High RE	0.063	0.059	0.079	0.105	0.104	0.089
	(0.389)	(0.423)	(0.420)	(0.283)	(0.293)	(0.455)
Leverage × ΔHP<0	0.078	0.078	0.091	0.011	0.009	0.000
	(0.126)	(0.127)	(0.182)	(0.873)	(0.893)	(0.998)
High RE × ΔHP<0	0.083**	0.086**	0.063	0.112*	0.116**	0.098
	(0.048)	(0.040)	(0.174)	(0.054)	(0.046)	(0.123)
HP		0.006***	0.004*		0.007***	0.006**
		(0.001)	(0.081)		(0.007)	(0.029)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,214	15,214	12,806	10,877	10,877	9,012
R-squared	0.286	0.287	0.295	0.353	0.354	0.366

Table VI: continued

Panel B: Short-Term Leverage

	(1)	(2)	(3)	(4)	(5)	(6)
Short-Term Leverage × High RE × ΔHP<0	-0.582*	-0.576*	-0.531	-0.714*	-0.717*	-0.674
	(0.059)	(0.062)	(0.101)	(0.084)	(0.082)	(0.114)
Leverage	-0.057	-0.053	-0.190*	0.007	0.011	-0.183*
	(0.501)	(0.531)	(0.067)	(0.937)	(0.906)	(0.089)
High RE	-0.007	-0.002	-0.010	-0.041*	-0.036	-0.033
	(0.705)	(0.915)	(0.569)	(0.078)	(0.121)	(0.170)
ΔHP<0	-0.008	-0.018	-0.019	-0.003	-0.014	-0.020
	(0.699)	(0.368)	(0.394)	(0.919)	(0.623)	(0.527)
Leverage × High RE	0.075	0.072	0.202	0.214	0.213	0.346
	(0.699)	(0.714)	(0.358)	(0.326)	(0.332)	(0.145)
Leverage × ΔHP<0	0.093	0.093	0.141	-0.182	-0.177	-0.044
	(0.512)	(0.515)	(0.423)	(0.360)	(0.376)	(0.868)
High RE × ΔHP<0	0.034	0.037	0.030	0.056	0.060	0.067
	(0.228)	(0.188)	(0.319)	(0.166)	(0.142)	(0.128)
HP		0.006***	0.004*		0.007***	0.006**
		(0.001)	(0.083)		(0.010)	(0.035)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,302	15,302	12,816	10,921	10,921	9,020
R-squared	0.285	0.286	0.295	0.354	0.355	0.367

Table VII: Extensive Margin

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is a dummy variable that takes a value of one if the client-supplier relationship exists in period *t*-1 and does not exist in period *t*, and the shock to real estate prices (ΔHP<0) occurs in period *t*-1. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. ΔHP<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	0.084**	0.083**	0.097***	0.055	0.054	0.097**
	(0.014)	(0.015)	(0.010)	(0.178)	(0.193)	(0.035)
High Leverage	0.024**	0.025**	0.047***	0.021	0.021	0.044***
	(0.024)	(0.018)	(0.000)	(0.107)	(0.105)	(0.002)
High RE	-0.014	-0.010	-0.006	-0.011	-0.008	-0.003
	(0.349)	(0.481)	(0.673)	(0.588)	(0.697)	(0.882)
ΔHP<0	0.019	0.016	0.018	-0.012	-0.016	-0.007
	(0.200)	(0.304)	(0.272)	(0.501)	(0.381)	(0.724)
High Leverage × High RE	0.009	0.008	-0.004	0.007	0.007	-0.013
	(0.653)	(0.685)	(0.850)	(0.793)	(0.784)	(0.627)
High Leverage × ΔHP<0	-0.056***	-0.056***	-0.060***	-0.038*	-0.037*	-0.053**
	(0.001)	(0.002)	(0.002)	(0.091)	(0.096)	(0.029)
High RE × ΔHP<0	-0.049**	-0.048**	-0.051**	-0.017	-0.016	-0.036
	(0.028)	(0.033)	(0.036)	(0.555)	(0.595)	(0.287)
HP		0.003**	0.003**		0.003*	0.003*
		(0.034)	(0.046)		(0.057)	(0.075)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	18,243	18,243	15,442	12,792	12,792	10,686
R-squared	0.369	0.369	0.385	0.442	0.443	0.452

Table VIII: Financial Crisis Period

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. In Panel A, the sample consists of yearly observations of Compustat supplier-client pairs in the 2007-2009 period. In Panel B, the sample consists of yearly observations of Compustat supplier-client pairs in the 2007-2011 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Great Recession, 2007-2009

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.216**	-0.218**	-0.226**	-0.293**	-0.294**	-0.278**
	(0.032)	(0.031)	(0.029)	(0.037)	(0.037)	(0.050)
High Leverage	0.017	0.015	0.048	0.002	0.001	0.055
	(0.747)	(0.768)	(0.369)	(0.975)	(0.989)	(0.441)
High RE	-0.091	-0.092	-0.075	-0.133*	-0.133*	-0.127
	(0.126)	(0.124)	(0.228)	(0.086)	(0.086)	(0.103)
ΔHP<0	-0.037	-0.042	-0.033	-0.046	-0.050	-0.028
	(0.312)	(0.277)	(0.409)	(0.357)	(0.341)	(0.592)
High Leverage × High RE	0.103	0.104	0.098	0.100	0.101	0.094
	(0.168)	(0.162)	(0.207)	(0.294)	(0.290)	(0.333)
High Leverage × ΔHP<0	0.023	0.025	-0.003	0.064	0.066	0.014
	(0.704)	(0.679)	(0.961)	(0.438)	(0.429)	(0.867)
High RE × ΔHP<0	0.165**	0.167**	0.170**	0.247**	0.249**	0.268**
	(0.024)	(0.023)	(0.026)	(0.016)	(0.015)	(0.011)
HP		0.001	-0.003		0.001	-0.001
		(0.749)	(0.448)		(0.841)	(0.870)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	2,855	2,855	2,509	2,106	2,106	1,824
R-squared	0.286	0.286	0.297	0.338	0.338	0.351

Table VIII: continued

Panel B: Real Estate Crisis, 2007-2011

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.185**	-0.188**	-0.193**	-0.201*	-0.200*	-0.187
	(0.035)	(0.032)	(0.032)	(0.082)	(0.084)	(0.108)
High Leverage	0.021	0.018	0.037	0.016	0.018	0.057
	(0.660)	(0.698)	(0.452)	(0.803)	(0.786)	(0.389)
High RE	-0.095	-0.096	-0.082	-0.143*	-0.142*	-0.131
	(0.133)	(0.129)	(0.200)	(0.088)	(0.089)	(0.102)
ΔHP<0	-0.002	-0.011	-0.005	-0.002	0.003	0.019
	(0.944)	(0.749)	(0.883)	(0.972)	(0.945)	(0.679)
High Leverage × High RE	0.118	0.121	0.120	0.116	0.116	0.109
	(0.108)	(0.101)	(0.110)	(0.229)	(0.233)	(0.262)
High Leverage × ΔHP<0	-0.006	-0.003	-0.032	-0.004	-0.006	-0.055
	(0.904)	(0.952)	(0.547)	(0.951)	(0.934)	(0.431)
High RE × ΔHP<0	0.124*	0.128*	0.124*	0.175*	0.174*	0.188**
	(0.086)	(0.077)	(0.085)	(0.073)	(0.077)	(0.046)
HP		0.002	-0.000		-0.001	-0.001
		(0.482)	(0.933)		(0.761)	(0.798)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	4,668	4,668	4,018	3,456	3,456	2,935
R-squared	0.289	0.289	0.293	0.339	0.339	0.344

Table IX: Supplier Market Share and Product Market Competition

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. In columns (1) and (2), the low and high market share groups consist of those suppliers that have market share (three-digit SIC) below and above the median. In columns (3) and (4), the low and high number of firms groups consist of those suppliers that are in industries (three-digit SIC) with number of firms below and above the median. In columns (5) and (6), the low and high 1 – Lerner Index groups consist of those suppliers that are in industries (three-digit SIC) with yearly median 1 – net margin below and above the median. In columns (7) and (8), the low and high 1 – net margin groups consist of those suppliers that have 1 – ratio of net income to sales below and above the median. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Market Share		Number of Firms		1 − Lerner Index		1 − Net Margin	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Leverage × High RE × ΔHP<0	-0.218*	-0.084	-0.113*	-0.248**	-0.076	-0.157*	-0.071	-0.213**
	(0.090)	(0.201)	(0.060)	(0.032)	(0.404)	(0.078)	(0.432)	(0.031)
High Leverage	0.006	0.002	-0.017	0.004	-0.002	-0.001	0.018	0.011
	(0.880)	(0.918)	(0.419)	(0.895)	(0.950)	(0.963)	(0.454)	(0.747)
High RE	-0.122**	-0.021	-0.042	-0.086*	-0.047	-0.052	-0.032	-0.120**
	(0.019)	(0.514)	(0.141)	(0.078)	(0.418)	(0.150)	(0.460)	(0.012)
ΔHP<0	-0.028	0.009	-0.008	-0.002	-0.021	-0.002	0.023	-0.057
	(0.638)	(0.771)	(0.771)	(0.972)	(0.642)	(0.959)	(0.524)	(0.367)
High Leverage × High RE	0.116*	0.019	0.021	0.134**	0.058	0.047	0.037	0.104*
	(0.100)	(0.579)	(0.537)	(0.024)	(0.328)	(0.284)	(0.496)	(0.057)
High Leverage × ΔHP<0	-0.024	0.005	0.016	0.003	0.012	0.001	-0.051	0.097
	(0.750)	(0.856)	(0.617)	(0.955)	(0.791)	(0.985)	(0.167)	(0.160)
High RE × ΔHP<0	0.168*	0.056	0.092*	0.131	0.090	0.098	0.100	0.135*
	(0.090)	(0.306)	(0.064)	(0.163)	(0.363)	(0.148)	(0.245)	(0.078)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,891	4,621	4,474	5,830	2,206	8,164	3,935	4,990
R-squared	0.362	0.420	0.416	0.341	0.392	0.346	0.408	0.365

Table X: Specificity in Supplier Product Market

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. In columns (1) and (2), the low and high R&D groups consist of those suppliers that have ratio of R&D expenditures to total assets below and above the median. In columns (3) and (4), the zero and positive patent counts groups consist of those suppliers that have number of patents filed equal to zero and greater than zero. In columns (5) and (6), the low and high intangibles groups consist of those suppliers that have ratio of intangibles to total assets below and above the median. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	R&D		Patent Counts		Intangibles	
	Low	High	Zero	Positive	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.255**	-0.044	-0.175*	-0.040	-0.388*	-0.009
	(0.011)	(0.604)	(0.074)	(0.844)	(0.100)	(0.892)
High Leverage	-0.052**	0.023	0.000	0.077*	-0.012	0.012
	(0.039)	(0.369)	(0.997)	(0.087)	(0.902)	(0.538)
High RE	-0.084*	-0.028	-0.080**	0.099	-0.032	-0.021
	(0.055)	(0.527)	(0.044)	(0.219)	(0.748)	(0.492)
ΔHP<0	-0.047	-0.003	-0.061	0.038	-0.109	0.012
	(0.363)	(0.944)	(0.281)	(0.580)	(0.343)	(0.711)
High Leverage × High RE	0.126***	0.002	0.048	-0.091	0.111	-0.016
	(0.006)	(0.979)	(0.300)	(0.348)	(0.348)	(0.659)
High Leverage × ΔHP<0	0.095	-0.027	0.068	-0.058	0.153	-0.026
	(0.103)	(0.510)	(0.246)	(0.482)	(0.443)	(0.388)
High RE × ΔHP<0	0.217**	0.008	0.147*	0.018	0.332**	0.008
	(0.018)	(0.902)	(0.053)	(0.895)	(0.033)	(0.883)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,989	6,889	4,379	2,132	1,627	7,423
R-squared	0.440	0.341	0.389	0.419	0.433	0.386

Table XI: Durable Goods

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. In columns (1) and (2), the durable goods and non-durable goods are based on the supplier Fama-French industry classification. In columns (3) and (4), the non-manufacturing and manufacturing industries are based on the supplier Fama-French industry classification. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Durable Goods	Non-Durable Goods	Non-Manufacturing Industries	Manufacturing Industries
	(1)	(2)	(3)	(4)
High Leverage × High RE × ΔHP<0	-0.149**	0.006	-0.111*	-0.497***
	(0.036)	(0.933)	(0.092)	(0.000)
High Leverage	0.004	-0.031	0.002	-0.024
	(0.865)	(0.267)	(0.934)	(0.546)
High RE	-0.053	-0.048	-0.065**	-0.008
	(0.107)	(0.320)	(0.046)	(0.855)
ΔHP<0	-0.009	-0.018	-0.006	-0.127*
	(0.814)	(0.641)	(0.866)	(0.054)
High Leverage × High RE	0.054	0.002	0.049	0.070
	(0.162)	(0.967)	(0.189)	(0.231)
High Leverage × ΔHP<0	0.008	0.012	-0.001	0.176**
	(0.846)	(0.808)	(0.974)	(0.040)
High RE × ΔHP<0	0.093	0.043	0.087	0.325**
	(0.121)	(0.489)	(0.117)	(0.011)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes
Observations	9,569	1,285	9,817	947
R-squared	0.357	0.268	0.350	0.420

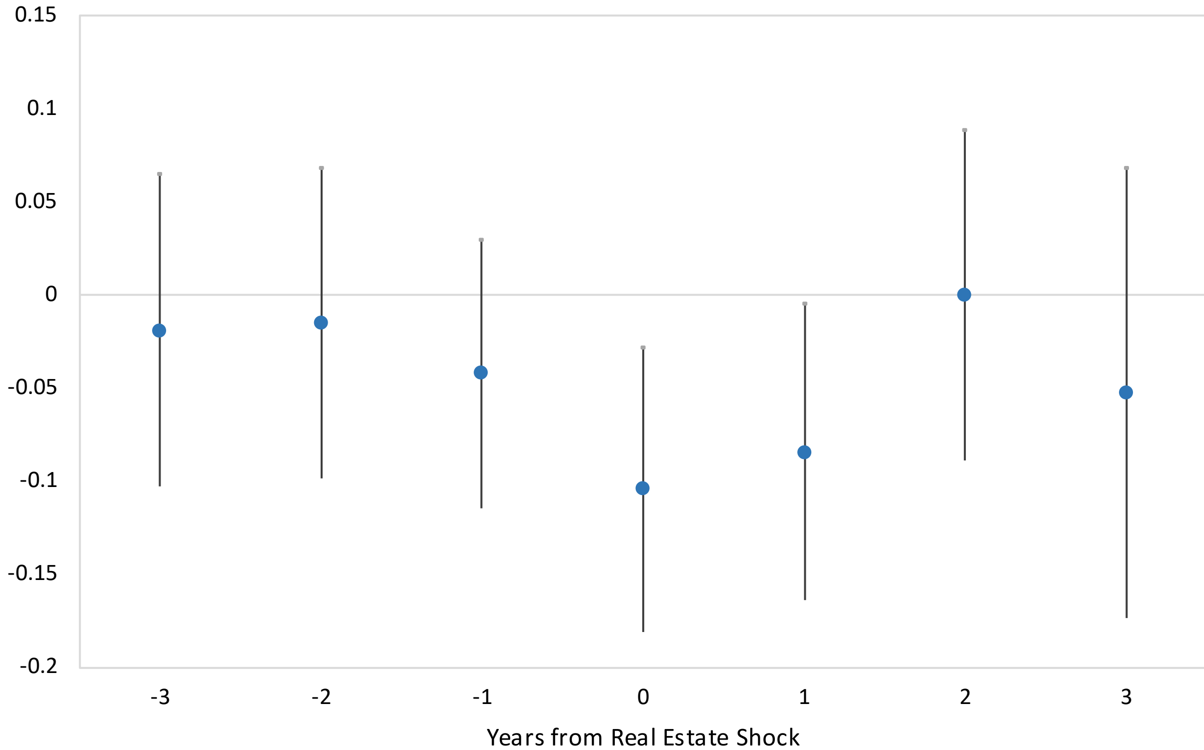
Table XII: Client-Supplier Relationship

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. In columns (1) and (2), the low and high supplier weight groups consist of those pairs that have ratio of sales between client and supplier divided by the cost of goods sold of the client (supplier weight) below and above median. In columns (3)-(6), the low and high supplier weight groups are further split by the median of the geographic distance between the supplier and client headquarters. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust p-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	All Firms		High Distance		Low Distance	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage x High RE x ΔHP<0	0.090	-0.188***	-0.140	-0.457**	0.238	-0.097
	(0.546)	(0.003)	(0.583)	(0.047)	(0.221)	(0.208)
High Leverage	0.037	-0.025	-0.023	-0.048	0.020	-0.005
	(0.346)	(0.239)	(0.675)	(0.161)	(0.746)	(0.880)
High RE	0.007	-0.121***	-0.007	-0.238***	0.070	-0.048
	(0.915)	(0.003)	(0.951)	(0.003)	(0.371)	(0.329)
ΔHP<0	0.033	0.037	0.127	0.059	0.078	0.007
	(0.658)	(0.237)	(0.307)	(0.191)	(0.554)	(0.880)
High Leverage x High RE	-0.016	0.104**	0.126	0.182*	-0.173	0.046
	(0.840)	(0.019)	(0.408)	(0.052)	(0.106)	(0.432)
High Leverage x ΔHP<0	-0.122	0.019	-0.059	0.031	-0.090	0.005
	(0.186)	(0.529)	(0.659)	(0.511)	(0.460)	(0.928)
High RE x ΔHP<0	0.008	0.102*	0.030	0.373*	-0.114	0.044
	(0.932)	(0.065)	(0.864)	(0.074)	(0.440)	(0.475)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,552	4,991	1,053	1,862	905	1,925
R-squared	0.401	0.446	0.464	0.456	0.444	0.466

Figure 1: Placebo Regressions

This figure shows the coefficient and 90% confidence intervals of the DDD variable, *High Leverage* × *High RE* × Δ*HP*<0, in ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is Δlog(*Sales*), defined as the change in the log of sales from supplier *i* to client *j* between years *t*+*k*-1 and *t*+*k* (k=-3,-2,...,+3). The horizontal axis represents the index *k*. *High Leverage* is a dummy variable that takes a value of one if the ratio of the book value of debt to assets in *t*-1 is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of property, plant, and equipment to assets in *t*-1 is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t* and *t*-1 in the house price index of the county where the supplier is located is negative, and zero otherwise. *HP* is the house price index at *t*-1 in the county where the supplier is located. The regressions include the same control variables and client-by-year fixed effects as for column (1) of Table II. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period.



Appendix

Table A.1: Variable Definitions

Variable	Definition
Δlog(Sales)	Change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t* (Compustat).
Leverage	Total debt, defined as debt in current liabilities plus long-term debt, divided by total assets (Compustat (DLC + DLTT) / AT).
High Leverage	Dummy variable that takes a value of one if Leverage is above the median, and zero otherwise.
Market Leverage	Total debt, defined as debt in current liabilities plus long-term debt, divided by market value of assets (Compustat (DLC + DLTT) / (DLC + DLTT + CSHO × PRCC_F).
High Market Leverage	Dummy variable that takes a value of one if Market Leverage is above the median, and zero otherwise.
KZ	Kaplan-Zingales index defined as -1.002 × Cash Flow + 0.283 × Tobin's q + 3.139 × Leverage − 39.368 × Dividends − 1.315 × Cash; Cash Flow is income before extraordinary items plus depreciation and amortization; Dividends is common and preferred dividends; Cash is cash and short term investments (all variables are scaled by PPE).
High KZ Index	Dummy variable that takes a value of one if the KZ index is above the median, and zero otherwise.
Short-Term Leverage	Short-term debt divided by total assets (Compustat DLC / AT).
High Short-Term Leverage	Dummy variable that takes a value of one if Short-Term Leverage is above the median, and zero otherwise.
HP	House price index (repeat-sales index) in county of firm's main headquarters (Federal Housing Finance Agency).
ΔHP	Change in house price index (HP) in percentage.
ΔHP<0	Dummy variable that takes a value of one if ΔHP is negative, and zero otherwise.
RE	Property, plant and equipment (PPE) divided by total assets (Compustat PPENT / AT).
High RE	Dummy variable that takes a value of one if RE is above the 75th percentile, and zero otherwise.
RE Adjusted	Property, plant and equipment (PPE) divided by total assets in year *t* times the average ratio of real estate to PPE in the 1976-1993 period (Compustat PPENT / AT × (PPENT − PPENLS - PPENME) / PPENT).
High RE Adjusted	Dummy variable that takes a value of one if RE Adjusted is above the 75th percentile, and zero otherwise.
Market RE	Market value of real estate assets in 1993, scaled by total assets, inflated by the change in house prices from 1993 to year *t.*
High Market RE	Dummy variable that takes a value of one if Market RE is above the median, and zero otherwise.
Commercial RE	Commercial value of real estate assets, based on transaction level information and computed using the true geographical location of the firms' real estate assets, divided by PPE (Real Capital Analytics).
High Commercial RE	Dummy variable that takes a value of one if Commercial RE is above the median, and zero otherwise.

Table A.1: continued

Variable	Definition
Assets	Total assets (Compustat AT).
Cash	Cash divided by total assets (Compustat CHE / AT).
Tobin's q	Total assets plus market value of equity minus book value of equity divided by total assets (Compustat AT + CSHO × PRCC_F – [AT – (LT + PSTKL) + TXDITC] / AT).
Distance	Distance between the counties of the supplier's headquarters and the client's headquarter in miles.
Market Share	Sales divided by total industry (three-digit SIC) sales.
Number of Suppliers	Number of firms in each industry (three-digit SIC).
Lerner Index	Median net margin in the industry (three-digit SIC).
Net Margin	Net income to sales (Compustat NI/SALE).
R&D	Research and development (R&D) expenditures divided by total assets (Compustat XRD / AT).
Patent Counts	Number of patents applied for with the USPTO.
Intangibles	Intangible assets to total assets (Compustat INTAN / AT).
Supplier Weight	Sales from supplier *i* to client *j* divided by the cost of goods sold of client *j*.

Internet Appendix for

"The Economic Costs of Financial Distress"

Cláudia Custódio
Imperial College Business School, CEPR, ECGI

Miguel A. Ferreira
Nova School of Business and Economics, CEPR, ECGI

Emilia Garcia-Appendini
University of Zurich

Table IA.1: Alternative Real Estate Measure

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the product of the ratio of PPE to total assets by the average industry-level ratio of real estate assets to PPE between 1976 and 1993 is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Regressions include the same firm-level control variables and fixed effects as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.144**	-0.145**	-0.106	-0.167*	-0.170*	-0.132
	(0.023)	(0.022)	(0.110)	(0.060)	(0.056)	(0.145)
High Leverage	0.005	0.007	-0.001	0.000	0.001	-0.003
	(0.699)	(0.602)	(0.955)	(0.998)	(0.972)	(0.895)
High RE	-0.059**	-0.054**	-0.037	-0.094**	-0.089**	-0.064
	(0.033)	(0.049)	(0.182)	(0.021)	(0.028)	(0.111)
ΔHP<0	-0.010	-0.021	-0.016	-0.010	-0.022	-0.019
	(0.641)	(0.343)	(0.511)	(0.737)	(0.481)	(0.579)
High Leverage × High RE	0.050	0.048	0.036	0.081**	0.081**	0.064
	(0.111)	(0.123)	(0.277)	(0.048)	(0.049)	(0.123)
High Leverage × ΔHP<0	0.007	0.007	-0.005	0.000	0.000	-0.009
	(0.737)	(0.738)	(0.840)	(0.990)	(0.992)	(0.785)
High RE × ΔHP<0	0.133**	0.138**	0.106*	0.160*	0.167**	0.162*
	(0.016)	(0.012)	(0.063)	(0.056)	(0.045)	(0.062)
HP		0.006***	0.004*		0.007***	0.006**
		(0.001)	(0.074)		(0.007)	(0.029)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,212	15,212	12,804	10,877	10,877	9,012
R-squared	0.286	0.287	0.295	0.353	0.354	0.366

Table IA.2: Expected Default Frequency

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High EDF* is a dummy variable that takes a value of one if the ratio of the expected default frequency is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High EDF × High RE × ΔHP<0	-0.056	-0.056	-0.051	-0.082	-0.082	-0.068
	(0.292)	(0.288)	(0.350)	(0.212)	(0.209)	(0.309)
High EDF	-0.016	-0.016	-0.002	0.006	0.007	0.025
	(0.328)	(0.339)	(0.927)	(0.772)	(0.752)	(0.296)
High RE	0.000	0.003	-0.006	-0.025	-0.022	-0.026
	(0.995)	(0.912)	(0.801)	(0.454)	(0.506)	(0.454)
ΔHP<0	-0.005	-0.010	-0.006	0.014	0.005	0.023
	(0.851)	(0.672)	(0.824)	(0.663)	(0.876)	(0.504)
High EDF × High RE	0.009	0.009	0.010	-0.004	-0.003	-0.001
	(0.756)	(0.754)	(0.751)	(0.928)	(0.950)	(0.972)
High EDF × ΔHP<0	0.004	0.004	-0.004	-0.032	-0.030	-0.047
	(0.892)	(0.871)	(0.899)	(0.377)	(0.403)	(0.221)
High RE × ΔHP<0	0.054	0.056	0.054	0.096*	0.099*	0.090
	(0.172)	(0.160)	(0.178)	(0.076)	(0.067)	(0.102)
ΔHP		0.003	0.003		0.005*	0.004
		(0.140)	(0.232)		(0.085)	(0.138)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	12,273	12,273	11,385	8,660	8,660	8,058
R-squared	0.296	0.296	0.303	0.367	0.368	0.372

Table IA.3: Interactions of Control Variables with House Price Index

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. *Tobin's q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
High Leverage × High RE × ΔHP<0	-0.088*	-0.119*
	(0.076)	(0.072)
High Leverage	-0.005	-0.007
	(0.755)	(0.758)
High RE Exposure	-0.019	-0.042
	(0.368)	(0.162)
ΔHP<0	-0.014	-0.019
	(0.577)	(0.586)
High Leverage × High RE	0.029	0.051
	(0.291)	(0.158)
High Leverage × ΔHP<0	0.003	0.001
	(0.922)	(0.986)
High RE × ΔHP<0	0.055	0.100*
	(0.139)	(0.070)
HP	-0.005	0.001
	(0.476)	(0.889)
Tobin's q	-0.001	0.017*
	(0.891)	(0.052)
Cash	-0.070	-0.066
	(0.463)	(0.597)
Assets (log)	0.009	0.005
	(0.157)	(0.565)
HP × Tobin's q	0.002*	0.001
	(0.057)	(0.613)
HP × Cash	0.001	-0.003
	(0.966)	(0.847)
HP × Assets (log)	0.001	0.001
	(0.518)	(0.634)
Client × Year FE	Yes	No
Supplier Industry × Client × Year FE	No	Yes
Observations	12,806	9,012
R-squared	0.295	0.366

Table IA.4: Sample with Sales Coverage Above 30%

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample is restricted to suppliers for which the sum of reported sales by client represents at least 30% of total sales. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.126*	-0.130*	-0.078	-0.191**	-0.200**	-0.147
	(0.076)	(0.068)	(0.301)	(0.045)	(0.037)	(0.144)
High Leverage	0.012	0.012	0.016	0.020	0.019	0.019
	(0.565)	(0.542)	(0.468)	(0.475)	(0.500)	(0.534)
High RE	-0.038	-0.033	-0.012	-0.061	-0.058	-0.031
	(0.197)	(0.246)	(0.680)	(0.149)	(0.162)	(0.458)
ΔHP<0	-0.026	-0.042	-0.026	-0.017	-0.033	-0.016
	(0.439)	(0.218)	(0.480)	(0.721)	(0.486)	(0.743)
High Leverage × High RE	0.001	0.000	-0.024	0.016	0.018	-0.013
	(0.986)	(0.999)	(0.527)	(0.742)	(0.718)	(0.812)
High Leverage × ΔHP<0	0.007	0.008	-0.016	0.005	0.007	-0.015
	(0.835)	(0.819)	(0.695)	(0.917)	(0.882)	(0.785)
High RE × ΔHP<0	0.077	0.082	0.054	0.101	0.111	0.080
	(0.144)	(0.118)	(0.312)	(0.155)	(0.117)	(0.293)
HP		0.009***	0.006*		0.010**	0.009*
		(0.003)	(0.094)		(0.032)	(0.082)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	8,595	8,595	7,327	5,914	5,914	4,974
R-squared	0.308	0.310	0.318	0.364	0.365	0.379

Table IA.5: Real Estate Assets Location

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) is negative, and zero otherwise. *HP* in Panel A is the lagged weighted average of the index in all states where firms own real estate assets. *HP* in Panel B is the lagged house price index in the county where the supplier is located. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample in Panel B excludes firms with Herfindahl-Hirschman Index (HHI) of real estate holdings by state below the median. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: HP Weighted by Real Estate Assets by State

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.211**	-0.212**	-0.203**	-0.220*	-0.216*	-0.179
	(0.022)	(0.021)	(0.031)	(0.060)	(0.065)	(0.135)
High Leverage	0.009	0.009	-0.004	0.025	0.026	0.015
	(0.637)	(0.641)	(0.845)	(0.357)	(0.326)	(0.571)
High RE	-0.032	-0.032	-0.029	-0.038	-0.035	-0.031
	(0.211)	(0.205)	(0.251)	(0.286)	(0.321)	(0.405)
ΔHP<0	0.066*	0.067*	0.053	0.119**	0.108**	0.090
	(0.054)	(0.061)	(0.165)	(0.015)	(0.036)	(0.103)
High Leverage × High RE	0.034	0.035	0.028	0.021	0.019	0.027
	(0.297)	(0.290)	(0.394)	(0.628)	(0.654)	(0.549)
High Leverage × ΔHP<0	0.037	0.036	0.046	0.016	0.018	0.040
	(0.416)	(0.421)	(0.329)	(0.788)	(0.762)	(0.521)
High RE × ΔHP<0	0.077	0.077	0.094	0.042	0.040	0.029
	(0.172)	(0.172)	(0.101)	(0.569)	(0.590)	(0.704)
HP		-0.000	0.000		0.001	0.001
		(0.884)	(0.705)		(0.426)	(0.234)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	6,965	6,965	6,419	4,775	4,775	4,386
R-squared	0.280	0.280	0.290	0.381	0.382	0.390

Panel B: Sample Excluding Firms with Diversified Locations of Real Estate Assets

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.281**	-0.261**	-0.237*	-0.482***	-0.462**	-0.426**
	(0.023)	(0.036)	(0.067)	(0.009)	(0.011)	(0.031)
High Leverage	0.003	0.007	-0.001	0.021	0.023	0.012
	(0.893)	(0.751)	(0.961)	(0.477)	(0.417)	(0.679)
High RE	-0.021	-0.013	-0.020	-0.048	-0.040	-0.065
	(0.533)	(0.700)	(0.543)	(0.262)	(0.343)	(0.155)
ΔHP<0	-0.057	-0.086	-0.089	-0.086	-0.120	-0.100
	(0.300)	(0.138)	(0.139)	(0.222)	(0.106)	(0.209)
High Leverage × High RE	0.020	0.017	0.015	0.020	0.019	0.046
	(0.597)	(0.648)	(0.693)	(0.714)	(0.731)	(0.439)
High Leverage × ΔHP<0	0.063	0.065	0.051	0.143	0.145	0.101
	(0.379)	(0.375)	(0.511)	(0.216)	(0.213)	(0.433)
High RE × ΔHP<0	0.071	0.078	0.078	0.200	0.211*	0.204
	(0.300)	(0.250)	(0.260)	(0.103)	(0.081)	(0.114)
HP		0.010**	0.007*		0.009**	0.005
		(0.011)	(0.057)		(0.036)	(0.228)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	3,656	3,656	3,213	2,260	2,260	1,988
R-squared	0.306	0.308	0.326	0.425	0.427	0.458

Table IA.6: Single Segment Suppliers

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Regressions include the same firm-level control variables and fixed effects as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample is restricted to suppliers with a single business segment. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.160**	-0.162**	-0.168**	-0.230**	-0.235**	-0.220**
	(0.047)	(0.046)	(0.042)	(0.029)	(0.028)	(0.042)
High Leverage	-0.006	-0.003	-0.020	-0.022	-0.021	-0.039
	(0.828)	(0.899)	(0.472)	(0.562)	(0.575)	(0.300)
High RE	-0.023	-0.017	-0.019	-0.051	-0.042	-0.046
	(0.499)	(0.625)	(0.578)	(0.364)	(0.446)	(0.388)
ΔHP<0	-0.056	-0.064	-0.055	-0.065	-0.078	-0.062
	(0.162)	(0.111)	(0.209)	(0.250)	(0.167)	(0.309)
High Leverage × High RE	0.072*	0.069	0.074*	0.104*	0.104*	0.108*
	(0.092)	(0.107)	(0.084)	(0.077)	(0.074)	(0.066)
High Leverage × ΔHP<0	0.048	0.046	0.035	0.056	0.053	0.044
	(0.276)	(0.296)	(0.468)	(0.359)	(0.396)	(0.511)
High RE × ΔHP<0	0.092	0.094	0.083	0.120	0.120	0.112
	(0.132)	(0.126)	(0.168)	(0.214)	(0.206)	(0.220)
HP		0.005	0.003		0.010**	0.009*
		(0.105)	(0.439)		(0.031)	(0.100)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	6,982	6,982	6,254	4,780	4,780	4,260
R-squared	0.313	0.314	0.324	0.356	0.357	0.369

Table IA.7: House Price Index by MSA

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the Metropolitan Statistical Area (MSA) where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.135***	-0.138***	-0.153***	-0.212***	-0.218***	-0.230***
	(0.007)	(0.006)	(0.006)	(0.003)	(0.002)	(0.004)
High Leverage	0.012	0.013	-0.000	-0.004	-0.004	-0.014
	(0.483)	(0.456)	(0.980)	(0.879)	(0.857)	(0.602)
High RE	-0.034	-0.031	-0.040	-0.075**	-0.072**	-0.079**
	(0.161)	(0.210)	(0.111)	(0.041)	(0.050)	(0.038)
ΔHP<0	-0.030	-0.039	-0.052*	-0.032	-0.043	-0.067*
	(0.215)	(0.117)	(0.059)	(0.322)	(0.194)	(0.063)
High Leverage × High RE	0.040	0.040	0.049	0.079*	0.080**	0.092**
	(0.169)	(0.175)	(0.123)	(0.050)	(0.046)	(0.036)
High Leverage × ΔHP<0	0.027	0.028	0.037	0.046	0.048	0.062
	(0.361)	(0.350)	(0.271)	(0.265)	(0.244)	(0.176)
High RE × ΔHP<0	0.073*	0.078**	0.092**	0.092	0.100*	0.135**
	(0.052)	(0.038)	(0.019)	(0.125)	(0.096)	(0.041)
HP		0.000**	0.000		0.000*	0.000
		(0.040)	(0.244)		(0.078)	(0.110)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	11,857	11,857	9,794	8,188	8,188	6,614
R-squared	0.303	0.303	0.313	0.366	0.367	0.383

Table IA.8: Small Suppliers in Large Counties

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample excludes suppliers in the top 5% of the total assets distribution, and only includes suppliers that are located in counties in the top 5% of the population distribution. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.147***	-0.147***	-0.142**	-0.189**	-0.190**	-0.173**
	(0.010)	(0.009)	(0.020)	(0.013)	(0.013)	(0.041)
High Leverage	0.004	0.006	-0.008	-0.001	-0.001	-0.010
	(0.790)	(0.700)	(0.641)	(0.962)	(0.981)	(0.689)
High RE	-0.025	-0.019	-0.017	-0.068**	-0.063*	-0.050
	(0.287)	(0.411)	(0.471)	(0.042)	(0.060)	(0.141)
ΔHP<0	-0.024	-0.035	-0.034	-0.031	-0.041	-0.037
	(0.353)	(0.185)	(0.222)	(0.395)	(0.269)	(0.361)
High Leverage × High RE	0.037	0.035	0.036	0.064	0.064	0.058
	(0.214)	(0.240)	(0.262)	(0.113)	(0.115)	(0.176)
High Leverage × ΔHP<0	0.014	0.014	0.007	0.004	0.004	-0.006
	(0.598)	(0.608)	(0.832)	(0.916)	(0.919)	(0.893)
High RE × ΔHP<0	0.090**	0.093**	0.084*	0.108*	0.112*	0.119*
	(0.041)	(0.035)	(0.063)	(0.081)	(0.070)	(0.088)
HP		0.007***	0.004		0.006**	0.006*
		(0.006)	(0.154)		(0.041)	(0.094)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	12,534	12,534	10,539	8,782	8,782	7,264
R-squared	0.294	0.295	0.304	0.359	0.359	0.372

Table IA.9: Sample Excluding Industries with Large Exposure to Real Estate

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Regressions include the same firm-level control variables and fixed effects as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample in each panel excludes an industry with a large exposure to real estate prices based on the *RE* variable. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Sample Excluding Energy

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.074	-0.074	-0.063	-0.108*	-0.111*	-0.094
	(0.134)	(0.132)	(0.241)	(0.072)	(0.066)	(0.166)
Observations	14,026	14,026	11,783	9,978	9,978	8,220
R-squared	0.275	0.276	0.285	0.345	0.346	0.356

Panel B: Sample Excluding Utilities

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.108**	-0.109**	-0.098**	-0.139**	-0.141**	-0.120*
	(0.020)	(0.019)	(0.047)	(0.026)	(0.024)	(0.070)
Observations	15,040	15,040	12,738	10,785	10,785	9,002
R-squared	0.285	0.285	0.294	0.352	0.353	0.366

Panel C: Sample Excluding Telecoms

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.078*	-0.079*	-0.072	-0.131**	-0.133**	-0.112
	(0.091)	(0.088)	(0.147)	(0.040)	(0.037)	(0.100)
Observations	14,817	14,817	12,501	10,649	10,649	8,852
R-squared	0.287	0.287	0.296	0.349	0.350	0.364

Panel D: Sample Excluding Shops

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.109**	-0.109**	-0.097*	-0.137**	-0.139**	-0.125*
	(0.021)	(0.020)	(0.053)	(0.028)	(0.026)	(0.061)
Observations	14,661	14,661	12,406	10,730	10,730	8,935
R-squared	0.286	0.287	0.294	0.351	0.351	0.364

Panel E: Sample Excluding Manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.116**	-0.117**	-0.091	-0.111*	-0.115*	-0.100
	(0.029)	(0.028)	(0.112)	(0.092)	(0.085)	(0.155)
Observations	13,160	13,160	11,144	9,817	9,817	8,200
R-squared	0.293	0.294	0.305	0.350	0.351	0.365

Table IA.10: Real Estate Measure Excluding Leases

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE (excluding leases) to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.126***	-0.126***	-0.113**	-0.151**	-0.155**	-0.140**
	(0.006)	(0.006)	(0.021)	(0.013)	(0.012)	(0.035)
High Leverage	-0.001	0.001	-0.009	-0.005	-0.005	-0.013
	(0.966)	(0.942)	(0.571)	(0.802)	(0.805)	(0.569)
High RE	-0.028	-0.022	-0.015	-0.063**	-0.058*	-0.046
	(0.198)	(0.292)	(0.473)	(0.039)	(0.054)	(0.143)
ΔHP<0	-0.010	-0.021	-0.016	-0.012	-0.024	-0.020
	(0.675)	(0.370)	(0.534)	(0.706)	(0.463)	(0.571)
High Leverage × High RE	0.043*	0.041	0.042	0.062*	0.063*	0.068*
	(0.099)	(0.108)	(0.123)	(0.075)	(0.070)	(0.070)
High Leverage × ΔHP<0	0.021	0.021	0.011	0.016	0.017	0.009
	(0.377)	(0.381)	(0.676)	(0.622)	(0.622)	(0.809)
High RE × ΔHP<0	0.071**	0.075**	0.058	0.096*	0.102**	0.099*
	(0.048)	(0.036)	(0.119)	(0.061)	(0.047)	(0.067)
HP		0.006***	0.004*		0.007***	0.006**
		(0.001)	(0.067)		(0.008)	(0.029)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,214	15,214	12,806	10,877	10,877	9,012
R-squared	0.286	0.286	0.294	0.353	0.354	0.366

Table IA.11: Sample Excluding Clients with Negative Real Estate Shocks

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE (excluding leases) to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample excludes clients with negative Δ*HP* and pairs in which client and supplier operate in the same state. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.216	-0.207	-0.088	-0.204	-0.187	-0.144
	(0.104)	(0.119)	(0.513)	(0.274)	(0.314)	(0.457)
High Leverage	0.009	0.011	-0.004	0.009	0.011	-0.005
	(0.569)	(0.493)	(0.819)	(0.690)	(0.613)	(0.804)
High RE	-0.021	-0.015	-0.007	-0.041	-0.030	-0.011
	(0.415)	(0.568)	(0.801)	(0.259)	(0.403)	(0.771)
ΔHP<0	-0.043	-0.050	-0.037	-0.020	-0.028	-0.030
	(0.289)	(0.213)	(0.416)	(0.743)	(0.638)	(0.646)
High Leverage × High RE	0.026	0.023	0.019	0.018	0.015	0.013
	(0.431)	(0.474)	(0.585)	(0.688)	(0.733)	(0.797)
High Leverage × ΔHP<0	0.018	0.016	-0.007	-0.002	-0.009	-0.009
	(0.700)	(0.738)	(0.904)	(0.971)	(0.899)	(0.909)
High RE × ΔHP<0	0.207**	0.208**	0.122	0.199	0.197	0.183
	(0.023)	(0.022)	(0.167)	(0.114)	(0.109)	(0.172)
HP		0.006**	0.003		0.010***	0.006*
		(0.032)	(0.262)		(0.005)	(0.087)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	6,854	6,854	5,784	4,814	4,814	3,969
R-squared	0.274	0.275	0.289	0.366	0.367	0.383

Table IA.12: Large Real Estate Shocks

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE (excluding leases) to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-1 and *t* in the house price index (*HP*) of the county where the supplier is located is below the 10th percentile (-3.3%), and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.091	-0.096	-0.103	-0.136*	-0.144*	-0.137
	(0.133)	(0.112)	(0.103)	(0.096)	(0.080)	(0.130)
High Leverage	0.002	0.004	-0.009	-0.004	-0.004	-0.012
	(0.877)	(0.768)	(0.519)	(0.808)	(0.815)	(0.537)
High RE	-0.010	-0.004	-0.005	-0.044*	-0.039	-0.031
	(0.619)	(0.834)	(0.814)	(0.097)	(0.140)	(0.274)
ΔHP<0	-0.035	-0.046*	-0.045*	-0.037	-0.048	-0.047
	(0.134)	(0.054)	(0.081)	(0.242)	(0.135)	(0.178)
High Leverage × High RE	0.014	0.013	0.018	0.033	0.034	0.037
	(0.540)	(0.569)	(0.474)	(0.284)	(0.274)	(0.268)
High Leverage × ΔHP<0	0.039	0.038	0.039	0.037	0.037	0.035
	(0.215)	(0.229)	(0.256)	(0.376)	(0.378)	(0.457)
High RE × ΔHP<0	0.024	0.031	0.022	0.096	0.104*	0.111
	(0.558)	(0.444)	(0.612)	(0.112)	(0.080)	(0.104)
HP		0.007***	0.004*		0.007***	0.007**
		(0.001)	(0.052)		(0.006)	(0.025)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,214	15,214	12,806	10,877	10,877	9,012
R-squared	0.286	0.286	0.295	0.353	0.354	0.366

Table IA.13: Lagged Real Estate Shocks

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *High Leverage* is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. *High RE* is a dummy variable that takes a value of one if the ratio of PPE (excluding leases) to total assets is above the 75th percentile, and zero otherwise. Δ*HP*<0 is a dummy variable that takes a value of one if the change between years *t*-2 and *t*-1 in the house price index (*HP*) of the county where the supplier is located is negative, and zero otherwise. Columns (3) and (6) include the same firm-level control variables as in Table II (coefficients not shown). All explanatory variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage × High RE × ΔHP<0	-0.112**	-0.114**	-0.118**	-0.114*	-0.119*	-0.125*
	(0.023)	(0.021)	(0.024)	(0.067)	(0.057)	(0.069)
High Leverage	0.005	0.006	-0.007	0.005	0.005	-0.004
	(0.739)	(0.663)	(0.638)	(0.785)	(0.781)	(0.830)
High RE	-0.025	-0.020	-0.018	-0.051*	-0.046	-0.039
	(0.239)	(0.355)	(0.397)	(0.089)	(0.123)	(0.202)
ΔHP<0	-0.018	-0.027	-0.026	-0.012	-0.021	-0.019
	(0.456)	(0.277)	(0.329)	(0.709)	(0.514)	(0.589)
High Leverage × High RE	0.030	0.029	0.034	0.041	0.042	0.048
	(0.246)	(0.259)	(0.221)	(0.231)	(0.217)	(0.190)
High Leverage × ΔHP<0	0.013	0.013	0.018	-0.009	-0.009	-0.003
	(0.604)	(0.596)	(0.491)	(0.781)	(0.783)	(0.932)
High RE × ΔHP<0	0.074**	0.077**	0.066*	0.088*	0.093*	0.106*
	(0.049)	(0.040)	(0.094)	(0.095)	(0.078)	(0.062)
HP		0.007***	0.004*		0.007***	0.007**
		(0.001)	(0.057)		(0.006)	(0.023)
Firm-Level Controls	No	No	Yes	No	No	Yes
Client × Year FE	Yes	Yes	Yes	No	No	No
Supplier Industry × Client × Year FE	No	No	No	Yes	Yes	Yes
Observations	15,233	15,233	12,827	10,896	10,896	9,029
R-squared	0.285	0.286	0.294	0.352	0.353	0.365