

WORKING PAPER

#648 | 2022



Indirect costs of financial distress

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This version: October 13, 2022

Abstract

We estimate the indirect costs of financial distress due to lost sales by exploiting real estate shocks and cross-supplier variation in real estate assets and leverage. We show that for the same client buying from different suppliers, the client's purchases from distressed suppliers decline by an additional 13% following a drop in local real estate prices. The effect is more pronounced in more competitive industries, manufacturing, durable goods, less-specific goods, and when the costs of switching suppliers are low. Our results suggest that clients reduce their exposure to suppliers in financial distress.

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

Keywords: Financial distress, Economic distress, Real estate prices, Supply chain

1. Introduction

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, firm 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 that occur prior to default, is to identify the costs driven by reputational concerns and impaired ability to conduct business. In the presence of information asymmetry, contractual frictions, or other conflicts between the firm and its stakeholders, a firm facing financial distress might experience a reduction in sales. In this paper, we estimate the indirect costs of financial distress that are associated with lost sales.

There are multiple economic theories suggesting reasons for why financial distress can generate indirect costs. First, customers might factor in higher risks of bankruptcy and reduce their exposure to failing firms by cutting their purchases (Titman, 1984; Opler and Titman, 1994). This might be particularly pronounced for durable goods 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 by using lower quality inputs 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 take predatory actions on their distressed competitors by offering lower prices, and clients may switch to these suppliers to benefit from lower mark-ups (Fudenberg and Tirole, 1986; Bolton and Scharfstein, 1990). Suppliers in financial distress might also be unable to extend trade credit or invest in working capital to maintain sales (Daripa and Nilsen, 2011; Almeida, Carvalho, and Kim, 2018). Finally, financial distress might have a negative effect on the reputation of a supplier, which might incentivize their clients to buy from other suppliers (Maksimovic and

Titman, 1991; Brown and Matsa, 2016).¹

We use a client-supplier pair panel of public firms in the United States sourced from the Compustat Segment database for the 2000-2015 period to estimate the decline in sales caused by financial distress. To identify the effects of a supplier's financial distress on its sales, we exploit local variations in real estate prices as shocks to the collateral value of firms. We use the value of real estate assets and leverage to determine the exposure to drops in real estate prices (the treatment). The value of real estate assets is proxied by the ratio of property, plant, and equipment (PPE) to total assets, knowing that real estate assets account for more than 80% of PPE (Cvijanovic, 2014). Leverage is proxied by the ratio of total debt to total assets in suppliers' balance sheets.² In summary, our estimate of the indirect costs of financial distress is the differential effect of real estate shocks on firms with high real estate assets and high leverage relative to otherwise similar firms.

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 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 policies. Because real estate assets can be used as collateral, firms with more leverage tend to be those that own more real estate as a fraction of their total assets and are therefore more exposed to adverse shocks. Real estate shocks have been shown to impact investment and financial policies through this 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 is in financial

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 feasible. Anecdotal evidence suggests that clients may bail out suppliers. PSA Group, the manufacturer 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).

² Our baseline results are robust to alternative measures of real estate assets (Chaney, Sraer, and Thesmar, 2012) and alternative measures of financial constraints, such as the market value of leverage, the Kaplan-Zingales (KZ) index of financial constraints (Kaplan and Zingales, 1997), and Merton's (1974) measure of distance to default.

distress.³ When clients observe these shocks, and if the cost of switching suppliers is sufficiently low, they might reduce their exposure to this supplier, 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 (Cohn and Wardlaw, 2016; Kini et al., 2017)).⁴ Consistent with this idea, we show that shocks to real estate prices lead to financial distress (relevance condition) as proxied by lower distance to default, higher probability of covenant violations, and to auditors expressing doubts about the viability of firms. These results are in line with Cvijanovic (2014) and provide support to the notion that negative real estate shocks hinder firms' ability to raise financing.

Our baseline regression includes client-by-time fixed effects, which implies that identification originates from the variation in the value of real estate assets and leverage across different suppliers of the same client each year.⁵ To the extent that the 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 to study the impact of bank liquidity shocks in which the comparison is across banks for the same borrower (Khwaja and Mian, 2008). Paravisini, Rappoport, and Schnabl (2020) argue that an additional identifying assumption of this approach is that changes in firms' credit demand are equally spread across all banks lending to the firm. In our case, this implies that changes in clients' purchases are equally spread across all suppliers, which is more plausible when suppliers are from the same industry. For this reason, in some regressions we further interact the client-by-time fixed effects with

³ Lian and Ma (2021) show that most of the debt is based on the value of cash flows from the firm's continuing operations (i.e., going-concern value) — cash-flow based lending (as opposed to asset-based lending). However, this debt may still be implicitly backed by tangible assets (Rampini and Viswanathan, 2020).

⁴ Our focus is on business-to-business transactions; therefore, we only consider firm-level demand, not consumer demand.

⁵ This approach is also motivated by evidence that suppliers' leverage decisions are also very likely influenced ex ante by the nature of their customer bases (Kale and Shahrur, 2007; Banerjee et al., 2008).

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, i.e., suppliers that are more affected by a decline in local real estate prices when compared to otherwise similar suppliers that are less affected. Our estimates are economically significant: a supplier in financial distress suffers a 13% stronger reduction in sales when there is a drop in local real estate prices.

To further validate that demand-side factors are not driving our results, and considering that clients and suppliers tend to co-locate, we estimate regressions with supplier county-by-year fixed effects, which absorb county-specific shocks. We also show that the effect is more pronounced when clients and suppliers are located further away from each other, 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 explains the reduction in suppliers' sales to a given client.

Another concern is that an improvement in a supplier's economic prospects could increase both its sales and local real estate prices, relative to other suppliers of the same client. Using the land supply elasticity instrument for real estate prices of Saiz (2010), we estimate our results in a subsample of counties with high land supply elasticity where real estate prices are less responsive to economic conditions. Our results continue to hold in this subsample, alleviating the concern that omitted economic conditions at the supplier's location may be driving our results.

We also examine the heterogeneity in the suppliers' industries. First, we examine whether the effect on sales is more pronounced in more competitive industries. In these 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: industries with more players, industries with low Lerner Index, and when the suppliers have low market share and low net margins.

Second, we find that the reduction in sales is larger for suppliers that produce durable goods and operate in manufacturing industries, which is consistent with the idea that this type of goods

require post-purchase service and clients might be concerned that the supplier will get liquidated.

Third, we examine whether the effect of financial distress on sales is more pronounced when the supplier produces a less-specific product and/or service (i.e., when the costs of switching suppliers are low). Barrot and Sauvagnat (2016) show that there are substantial switching costs between trade partners due to input specificity and can explain the propagation of shocks in firm networks. We employ three measures of the supplier's specificity: R&D expenditures, patent counts, and intangible assets. R&D expenditures and patent counts capture the importance of relationship-specific investments and restrictions on finding alternative sources. Intangible assets are associated with a more specific and differentiated input. We find that the estimated indirect costs of financial distress are larger when suppliers produce less-specific goods.

Finally, 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. This is consistent with the notion that clients want to hedge against a disruption in a supplier's production.

The heterogeneous effects suggest that the indirect costs of financial distress are driven by clients reducing purchases from distressed suppliers, rather than by suppliers reducing their supply of products and/or services (at least with the same quality). We further investigate this question by exploiting within-firm variation in (distressed) multi-segment firms with high real estate assets and high leverage. If the reduction in sales is client initiated, durable goods business segments are expected to be relatively more affected than non-durable goods business segments within the same firm. If the reduction in sales is supplier initiated, the effects are expected to be more homogeneous across business segments. We find that our estimated effect is more pronounced in durable goods segments, which indicates that the indirect costs of financial distress are driven mostly by clients reducing their exposure to distressed suppliers.

Consistent with this interpretation, we do not find evidence that the reduction in sales is driven by the inability of financially distressed suppliers to extend trade credit or invest in working capital. We test these channels by exploiting heterogeneity in trade credit provision and investment in inventory and fixed assets at the industry level. We find that the decline in sales due to financial

distress is similar across industries with different levels of trade credit, inventory, and investment.

Overall, our results suggest that a supplier's financial distress driven by local real estate prices can generate significant costs as measured by lost sales. Considering a firm value to sales ratio of 1.47 (i.e., the median in our sample), our baseline estimate implies a 19.6% ($13.3\% \times 1.47$) larger reduction in firm value for distressed firms.⁶ The magnitude of this estimate is line with previous studies, which find indirect costs of financial distress between 6% and 20% of firm value (Opler and Titman, 1994; Andrade and Kaplan, 2002). We conclude that the indirect costs of financial distress are sufficiently sizable to be an important consideration in capital structure decisions.

Our paper contributes to the literature on the differences between financial distress and economic distress (Opler and Titman, 1993, 1994; Denis and Denis, 1995; Andrade and Kaplan, 1998) and measures the economic costs of financial distress (Almeida and Philippon, 2007; Hortacsu et al., 2013; Nocke and Thanassoulis, 2014; Giroud and Mueller, 2017; Gilchrist et al., 2017; Kim, 2018; Sautner and Vladimirov, 2018; Baghai et al., 2021). We contribute to this literature by estimating the costs of financial distress associated with lost sales by using client-supplier pairs data on several industries. We perform our estimations with client-by-year fixed effects, which holds the total demand of a client fixed each year. We provide evidence of a causal effect of financial distress on economic performance that is driven by differences in financial distress across suppliers, rather than demand shocks.

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). Cvijanović (2014) shows that leverage increases with collateral value, but Campello et al. (2021) show that firms take on new debt following an increase in the value of their real estate, but through unsecured debt, rather than

⁶ To assess the economic effect of our estimates, we also estimate the effect of a reduction in house prices on the distance to default on a subsample of firms with high leverage and high real estate assets. We find that a negative real estate shock decreases the distance to default by 6% evaluated at the mean.

mortgages or any other form of secured debt. We contribute to this literature by estimating the indirect costs of financial distress due to real estate shocks through the balance sheet channel.⁷

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 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.

2. Data and Methodology

2.1. 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. 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 client names to Compustat data to obtain their balance sheet information. Table A.1 in the Appendix provides the variable definitions.

In our estimations, we use real estate prices as shocks to the collateral value of firms with real estate assets to estimate their sensitivity to financial distress. Indeed, in the presence of incomplete contracts, lower collateral values affect the likelihood of a firm's financial distress by increasing

⁷ 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.

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.

To evaluate a firm's indirect costs of financial distress, we use the supplier's leverage as our main measure of financial constraints and the change 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 shocks. 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 them. 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.

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.⁸ 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 et al. 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 only \$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

⁸ 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.

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 each year using alternative measures. We use 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.

2.2. Summary Statistics

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.

Panels A and B of Table 1 contain the descriptive statistics. Panel A presents 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 some highly levered firms. The average value of our main variable for real estate assets (*RE*), which corresponds to the ratio of PPE to total assets, is 23.3%, 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 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 account on average (median) for 66.4% (81.1%) of PPE in 1976-1993.

Panel B of Table 1 shows that the clients in our sample are larger than their suppliers as proxied by assets. This is due to regulation SFAS 14, which only requires disclosure 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 have lower market valuations 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.

Table IA.1 in the Internet Appendix contains a year-by-year description of our sample; it 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 large time series variation in real estate asset prices. 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; 29.1% of all the observations correspond to firm-years with negative changes in local house prices. Figure IA.1 in the Internet Appendix shows that there is also a large geographic variation in the change in real estate prices across counties. Figure IA.2 shows the distribution of the estimated β coefficient (left-hand panel) and the R^2 (right-hand panel) of regressions of county-level returns for real estate on the returns of S&P/Case-Shiller U.S. National Home Price Index for the sample of all U.S. counties from 1986 to 2016 at the yearly frequency. County level real estate returns are mostly explained by idiosyncratic factors as opposed to systematic factors, which is consistent with the notion that real estate shocks are mostly idiosyncratic.

2.3. 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. This empirical strategy follows Khwaja and Mian (2008) and is extensively used in the banking literature to study the impact of bank liquidity shocks in which the comparison

is across banks for the same borrower.⁹ To investigate our hypothesis, we use a triple differences estimator:

$$\begin{aligned} \Delta \ln(\text{Sales})_{ijt} = & \beta(\Delta HP < 0)_{it} \text{High RE}_{i,t-1} \text{High Leverage}_{i,t-1} \\ & + \gamma X_{i,t-1} + \delta_{jt} + \varepsilon_{ijt}, \end{aligned} \quad (1)$$

where i denotes suppliers and j denotes clients. The dependent variable ($\Delta \ln(\text{Sales})_{ijt}$) measures the percentage change in the supplier's sales to each client, which is our measure of economic distress.¹⁰ $(\Delta HP < 0)_{it}$ is a dummy variable that takes a value of one if the house price index (HP) in the county where supplier i is located drops between year $t-1$ and year t , and is zero otherwise. $\text{High RE}_{i,t-1}$ 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. $\text{High Leverage}_{i,t-1}$ is a dummy variable that takes a value of one if the supplier i ratio of total debt to total assets (book leverage) is above the median of the distribution and is our main measure of financial constraints. In extensions to our baseline regressions, we also consider continuous measures of changes in real estate price, real estate exposure, and leverage. $X_{i,t-1}$ is a vector of supplier controls in year $t-1$, and δ_{jt} is a client-by-year fixed effect.

Our coefficient of interest is the β coefficient (triple interaction term). This coefficient estimates whether the difference between the response of firms with high real estate assets and high leverage relative to otherwise similar firms following a real estate shock is significant. A negative coefficient would indicate that clients reduce their purchases from suppliers more affected by real estate shocks (i.e., highly levered firms with large real estate assets) and would support the notion that clients typically reduce their exposure to suppliers in financial distress.¹¹

Our client-supplier data allow us to include client-by-year fixed effects in equation (1), which

⁹ Using firm changes as the dependent variable for cross-sectional comparisons is also common in corporate finance settings (e.g., Banerjee and Duflo, 2014).

¹⁰ We require non-missing sales data in two consecutive years to calculate the change in sales for each client-supplier pair.

¹¹ An alternative interpretation for a negative coefficient, which is also consistent with a cost of financial distress, is that sale prices decrease more for distressed firms.

ensures that identification comes from the variation, within the same year, of shocks to real estate across the suppliers of a given client. Client-by-time fixed effects absorb all unobserved heterogeneity at the client level in each 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 differences in financial distress across suppliers.

In all regressions, we estimate coefficients for the variables $(\Delta H P < 0)_{it}$, $RE_{i,t-1}$, 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 the house price index (*HP*). In our baseline regressions, we cluster standard errors at the supplier level as they correspond to the variation we explore in the main explanatory variable.

2.4. Identifying Assumptions

2.4.1. Balance Tests

We conduct balance tests to compare the observable characteristics of high leverage and high real estate assets firms located in counties that suffered a real estate shock $\Delta H P < 0$, with high leverage and high real estate assets firms located in counties that did not suffer a real estate shock $\Delta H P \geq 0$. Our main estimates assume these two groups are otherwise similar absent the real estate shock. We report *t*-tests of the differences as well as normalized differences in Table 2. Panel A displays the results of a comparison of the characteristics of the two groups in our supplier-client matched sample, while Panel B provides the results for a similar comparison for all Compustat firms in our sample period. The results show that firms experiencing a negative change to real estate prices ($\Delta H P < 0$) and other firms ($\Delta H P \geq 0$) are virtually identical in terms of average leverage and real estate assets, as expected. However, they are also similar in terms of other observable characteristics (*Assets*, *Tobin's q*, and *Cash*). The normalized difference of the average values of these variables is lower than the threshold value of 0.25, as required for common support (Imbens

and Wooldridge, 2009).¹²

2.4.2. Relevance Condition

Another identifying assumption we make is that drops in the value of real estate assets lead to financial distress in firms with high leverage and high real estate assets. Table 3 shows the estimates of firm-level regressions using different measures of financial distress between years t and $t+1$ as the dependent variable. First, we use the change in the distance to default ($\Delta Distance\ to\ Default$) as the dependent variable (column 1). *Distance to Default* is based on Merton's (1974) bond pricing model. We estimate this measure following the naïve approach proposed by Bharath and Shumway (2008). Second, we use *Covenant Violation* as the dependent variable (column 2). *Covenant Violation* is a dummy variable that takes a value of one if the firm violated at least one debt covenant and zero otherwise. We obtain covenant violations registered with the U.S. Securities and Exchange Commission (SEC) from Amir Sufi's publicly available data set. Finally, we use *Doubts of Going Concern* as the dependent variable (column 3). This is a dummy variable that takes a value of one if the auditor expressed doubts of the viability of the firm as a going concern and zero otherwise. We obtain information on the auditor's opinion from the Key Developments data available through Capital IQ.¹³

When we use *Distance to Default* as our dependent variable, the coefficient of the triple interaction is negative and significant, which indicates that the distance to default decreases (i.e., credit risk increases) more for firms with high leverage and high real estate assets. When we use *Covenant Violation* and *Doubts of Going Concern* as dependent variables, the triple interaction coefficient is positive and significant, indicating that high leverage and high real estate asset firms are more likely to experience covenant violations and going concern audit opinions. An auditor that raises doubts of the viability of a firm as a going concern considers “soft” information obtained

¹² Imbens and Wooldridge (2009) recommend focusing on the normalized difference, rather than on the t -statistic for the difference in averages, because large samples mechanically lead to large t -statistics.

¹³ The Key Development data contain information for doubts on going concern from 2003 onwards, and on firm defaults on debt obligations from 2006 onwards. We therefore restrict the analyses of these two measures to the years in which these events are non-missing in the Key Development data.

through the auditing process, which is also the type of information that clients might perceive during business transactions with suppliers.

Overall, these results provide support for our assumption that firms with high (low) leverage and high (low) real estate assets are more likely (unlikely) to face financial distress when there is a drop in local real estate prices.¹⁴

2.4.3. External Validity

Our sample covers a wide variety of firms and industries that are representative of developed countries. The client-supplier data are restricted to publicly traded firms in Compustat, thus they do not contain clients that are private firms, governments, or firms based outside of the U.S. The SFAS 14 and 131 reporting regulations do not allow us to identify clients that buy small amounts or aggregate clients. Overall, our results are informative of the behavior of large publicly traded firms buying from a heterogeneous set of suppliers in terms of size and industry.

3. Results

3.1. Main Results

Table 4 presents the results of estimating our main regression at the supplier-client level in equation (1) using different variables to measure the change in real estate prices. In the regressions for columns (1)-(3), ΔHP 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 the regression for column (4), ΔHP is a dummy variable that takes a value of one if the change between years $t-1$ and t in HP is lower than the 10th percentile of the distribution (-3.3%), and zero otherwise. In the regression for column (5), ΔHP is the continuous change in real estate prices. In the regression for column (6), ΔHP is a dummy variable that takes

¹⁴ We also consider other direct measures of distress, such as bankruptcy and default. However, bankruptcies and defaults are rare events so there is not much variation (on average we observe around 40 bankruptcies and less than 20 defaults on debt obligations per year). Moreover, as mentioned before, the interpretation of indirect costs of financial distress does not require financial distress to materialize in an extreme event such as default or bankruptcy.

a value of one if the change between years $t-2$ and $t-1$ in HP is negative, and is zero otherwise. The dependent variable in all specifications is the percentage change in the supplier's sales to each client ($\Delta \ln(Sales)_{ijt}$).

The results in column (1) show that the coefficient of the triple interaction ($High\ Leverage \times High\ RE \times \Delta HP < 0$) is negative and statistically significant.¹⁵ The effect of financial distress on a supplier's sales is also economically significant. When there is a drop in county-level house prices, sales decline 10.4% more for high real estate assets and high leverage firms than otherwise similar firms. This estimate is plausibly driven by a firm's impaired ability to conduct business when it is in financial distress due to reputational concerns.

In columns (2) and (3), we present estimates of the regression for column (1) but substituting 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.¹⁶ 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 triple interaction coefficient are -13.3% and -11.9%, 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.¹⁷

Column (4) presents the estimates of a similar regression using a dummy that takes the value of one for larger decreases in house prices, $\Delta HP < -3.3\%$ (which corresponds to the 10th percentile in the distribution of ΔHP). The results are similar as before, with a coefficient of -0.136 and a p -value of 0.096. We next use the continuous change in house prices, ΔHP , rather than a dummy

¹⁵ We also estimate regressions using the *High Leverage* dummy as the only explanatory variable. The coefficient is negative (-0.014) and significant at the 10% level, consistent with a negative correlation between sales and leverage. We similarly obtain a negative and significant coefficient when we use a continuous leverage variable as the only explanatory variable (coeff. = -0.078, p -value = 0.000).

¹⁶ The point estimates are of similar magnitude when we use three-digit SIC codes. Table IA.2 in the Internet Appendix shows these results.

¹⁷ Table IA.3 in the Internet Appendix shows the results of our baseline regression when we cluster standard errors at the county level (Panel A) and double cluster at the client and supplier level (Panel B). Standard errors are similar to those in baseline regressions when we cluster at the county level and smaller in all specifications when we double cluster at the client and supplier level.

variable. In column (5), the estimated triple interaction coefficient is statistically significant at conventional levels. We then we measure house price shocks as a dummy variable taking a value of one if house prices fell between years $t-2$ and $t-1$, i.e., the year prior to change in sales. In column (6), the triple interaction coefficient implies a differential drop in sales of 11.4% for distressed firms, which is statistically significant (p -value = 0.067).

We next provide some guidance for interpreting the remaining coefficients in the regression. For all the interaction terms, we compare the firms for which the interaction is one with our baseline case, which is a low levered firm with low real estate holdings in a county without a drop in real estate prices. More generally, we analyse eight groups of firms, which correspond to the different combinations of the three dummy variables: *High Leverage*, *High RE*, and $\Delta HP < 0$. The total effect on sales for each of these groups corresponds to the sum of the coefficients for which the dummy variable is one.

3.2. Alternative Measures of Real Estate Assets

In Table 5, we consider alternative measures for the suppliers' real estate assets. In column (1), 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*). The sample size shrinks to less than 10% of the sample of our baseline estimates in Table 4, but the estimated coefficient is of the same order of magnitude to what is in Table 4, suggesting that a supplier with higher exposure to county-level housing shocks suffers a -14.8% stronger reduction in sales when there is a drop in local house prices, relative to another supplier in the same industry with lower exposure to these shocks.

In column (2), we examine real estate exposure using commercial real estate data (Campello, et al., 2021), as opposed to residential housing, obtained from Real Capital Analytics. This measure is based on transaction-level information and is calculated using the geographical location of the

firm's real estate assets.¹⁸ In column (3), 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 1976-1993 period (*Adjusted RE*); the book value of real estate assets is defined as PPE net of machinery, equipment, and leases. The sample for these estimations is reduced by more than half relative to our baseline estimation, as we impose the restriction that the firm was active in 1993. By construction, this sample is selected towards older firms, which are likely to be less financially constrained (Hadlock and Pierce, 2010). In the regression for column (4), we use an industry adjusted measure of real estate assets (*Industry RE*). This measure imputes the missing value of real estate assets (post 1993) as 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.

Overall, our results in Table 5 are robust to using alternative measures of real estate assets. The coefficients are of similar magnitude to those in Table 4 but some are estimated with less precision due to the smaller sample size when using alternative measures.¹⁹

3.3. 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 each 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

¹⁸ We thank Eva Steiner for sharing data on the market value of commercial real estate. For consistency with the analysis in Campello et al. (2021), we winsorize this variable at the 5% level.

¹⁹ The coefficients in Table 5 correspond to the specification in column (2) of Table 4.

specification used to generate the results in column (2) of Table 4. We estimate the coefficient of the triple interaction, $High\ Leverage \times High\ RE \times \Delta HHP < 0$, in regressions in which we fix the real estate shock at $t=0$, and vary the dependent variable over a period between -3 and +3 years. In our identification strategy, we assume that purchases for a firm's products or services would be the same for firms with different levels of real estate assets and leverage in the absence of the real estate shock. To study the parallel trends assumption, we evaluate whether the trends in sales for products or services for high real estate assets and high leverage relative to otherwise similar firms are the same before the real estate shock.

Figure 1 shows the coefficients of the triple interaction and their 90% confidence intervals. We find no evidence of preexisting differential trends in sales. The estimated coefficient is not statistically significant from year -3 to year -1. The coefficient at $t=0$ is -0.133, as shown in Table 4, and the coefficient at year +1 is also negative and significant. The effect does not persist beyond two years of the shock.

3.4. Local Economic Conditions

In this section we address the concern that an improvement in a supplier's economic prospects could increase both its sales and the local real estate prices relative to other suppliers of the same client. This should be more of a concern in regions where real estate prices are likely to be more responsive to economic prospects. Following Saiz (2010), who uses land supply elasticity as an instrument for real estate prices, we estimate equation (1) using a subsample of counties with high land supply elasticity where real estate prices are less responsive to the supplier's local economic conditions.²⁰ If local economic conditions are mostly driving our results, we should find that the treatment effect is much weaker, or not significant in this subsample. This is not what we find. Column (1) in Table 6 shows our estimates for a subsample of suppliers located in counties with

²⁰ This instrument is difficult to apply directly to drops in real estate prices, which is our variable of interest ($\Delta HHP < 0$)_{it}. Adelino, Schoar, and Severino (2015) argue that an increase in housing demand can translate into either higher house prices in inelastic areas or an expansion of housing volume in elastic areas. In contrast, a drop in housing demand does not lead to the destruction of housing stock, and thus prices drop in both inelastic and elastic areas.

high land supply elasticity (elasticity above one). Our point estimate of the triple interaction coefficient in this subsample (-11.8%) is close in magnitude to that in our baseline specification.²¹

In column (2) of Table 6, we report the results of estimating equation (1) 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 is the direct cause of 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 reverse causality concerns. We find that the triple interaction coefficient for this subsample is -19% and statistically significant at 5% level.

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. Column (1) in Table IA.4 in the Internet Appendix shows that the triple interaction coefficients are similar to those in Table 4.

A more general concern is that negative real estate shocks could affect different firms in our sample differently. For instance, negative real estate shocks might affect small and large firms differently, and because size is correlated with financial constraints this heterogeneous response of firms of different size could be being captured by our estimate. To address this concern, we augment the regressions by adding the interaction of all firm controls with each of the main explanatory variables: *High Leverage*, *High RE* and $\Delta HP < 0$. The results are in column (2) of Table IA.4 in the Internet Appendix. Our main results remain unchanged. We conclude that the differential response to real estate prices across suppliers with different characteristics can be attributed to the real estate collateral channel.

A key identifying assumption is that declining real estate prices in the supplier's headquarter

²¹ We update the Saiz (2010) housing supply elasticity data for housing elasticities to cover our 2000-2015 sample period. We thank Manuel Adelino for providing us with the updated data.

city induce financial distress, particularly among the most highly leveraged suppliers. A growing literature links firms' fundamentals to city-level measures of stock prices (e.g., Tobin's q), real estate prices, and other city-level variables (Dougal, Parsons, and Titman, 2015, 2022). Therefore, one concern is that decreases in real estate prices in a supplier's city could be indicative of the supplier's general prospects and/or financial health, irrespective of their debt ratio. We explore this issue by regressing changes in supplier sales on *High RE*, $\Delta HP < 0$, and their interaction. In Table IA.5 in the Internet Appendix, we find that the interaction term is not statistically significant, suggesting that this mechanism is not driving our results.²²

Taken together, the results in this section mitigate the concern that our results are mostly driven by omitted economic conditions at the location of the supplier.

3.5. Supplier-Client Location

Clients and suppliers may be located close to each other (Ellison, Glaeser, and Kerr, 2010). To the extent that local real estate shocks affect local clients' demand, the co-location of clients and suppliers could explain part of the decrease in suppliers' sales. To address this concern, we add supplier county-by-year fixed effects to the regressions to capture any source of local time-varying unobserved heterogeneity, such as a local economic shock. Panel A of Table IA.6 in the Internet Appendix presents the estimates. We find that the triple interaction coefficient is negative and significant. The magnitude of the effect is similar to that in Table 4 at about -17%.

In Panel B of Table IA.6 in the Internet Appendix, we present regression results for the subsamples of client-supplier pairs in which the geographic distance between supplier and client is below the median (low distance sample in column (1)) and above the median (high distance sample in column (2)). We find that the triple interaction coefficient is negative but not statistically significant for client-suppliers located closer to each other (low distance sample). By contrast, the

²² A related concern is that the double interaction term $High\ RE \times \Delta HP$ is positive and statistically significant in some specifications of Table 4, which might suggest that minimally leveraged suppliers owning real estate in struggling cities are gaining sales. However, the effect for low-levered and high real estate assets firms in counties with negative changes to real estate prices (given by the sum of the coefficients $High\ RE \times \Delta HP$, $High\ RE$, and ΔHP) is positive but statistically insignificant.

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. Less informed clients might not be able to distinguish between temporary financial distress triggered by a real estate shock and more fundamental problems. Thus, they may want to reduce their exposure to these suppliers, rather than risk future supply disruptions and/or supplier failure. 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.

3.6. Heterogeneity

In this subsection, we use insights from different theories to examine the heterogeneity of the indirect costs of financial distress. We test several empirical predictions.

3.6.1. Supplier Market Share and Product Market Competition

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 (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 on 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 7 present the results of regressions with supplier industry-by-client-by-year fixed effects for groups of suppliers with lower and higher than median values, respectively, in the distribution of the market share. We find that the negative effect of financial distress is only statistically and economically significant for suppliers with low market share. The decrease in sales is much less pronounced and statistically insignificant for 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 them. Moreover, financially distressed suppliers 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, $1 - \text{Lerner index}$ (where the Lerner index is the median net margin in each industry and year), and $1 - \text{net margin}$ (at the firm level). Columns (3)-(8) in Table 7 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 a more pronounced negative effect of financial distress for suppliers that operate in more competitive industries, i.e., high number of firms, high $1 - \text{Lerner index}$, and high $1 - \text{net margin}$. The coefficient of the triple interaction term ranges from -25% to -16% 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.

3.6.2. Durable Goods

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 of its product, this might have a more serious and longer impact for durable goods. Therefore, 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. Table 8 presents the results. Columns (1) and (2) show that the coefficient of the triple interaction is negative and significant in the case of durable goods and not statistically significant in the case of non-durable goods, respectively. Columns (3) and (4) show, respectively, that the negative effect of financial distress is more pronounced for suppliers in the manufacturing sector at -49.7%, while the effect is -11.1% in the non-manufacturing sector. This difference is statistically significant at the 1% level.

3.6.3. Specificity in Supplier Product Market

We next test the prediction that the negative effect of financial distress on supplier's sales should be more pronounced when the supplier produces a less-specialized product. We construct three measures of supplier's product specificity: ratio of R&D expenditures to assets; 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 9 presents the results. Columns (1) and (2) show that according to the median value of its distribution, the coefficient of the triple interaction is -25.5% and statistically significant for the suppliers with low R&D expenditures and not statistically significant in the group of suppliers with high R&D expenditures, respectively; the difference in coefficients between the two columns is significant at the 10% level. Columns (3) and (4) show that the negative effect of financial distress is significant at -17.5% for suppliers with no patents, while the effect is insignificant for suppliers with patents, respectively. Columns (5) and (6) show, respectively, that the effect of financial distress is only significant in the group with low intangibles at -38.8%, while the difference in coefficients relative to the high intangibles group is significant at the 10% level. These findings indicate that financial distress is more pronounced when the supplier produces a less-specific product, which is easier to replace with another supplier.²³

²³ The results are also 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.

3.6.4. Client-Supplier Relationship

If there is a strong relationship and dependence between client and supplier, it is more likely that a client will attempt to reduce its exposure to a distressed supplier preemptively to avoid a potential supply chain disruption. However, a client may find it harder to substitute a supplier with whom they have a stronger relationship because switching costs are higher. Therefore, we study the heterogeneity of the costs of financial distress based on the strength of the client-supplier relationship. 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 to the client (supplier weight). Table IA.7 in the Internet Appendix presents the results. Column (1) shows that the negative effect of financial distress on sales is more pronounced when the supplier weight is higher (i.e., the client is more dependent on a particular supplier), which is consistent with the notion that clients want to hedge against a future supply disruption, despite higher switching costs.

Because this result is at odds with the results in subsection 3.5, where we find that clients are more likely to switch when switching costs are low as proxied by geographical distance, we further explore this heterogeneity including the geographical dimension. We conjecture that precautionary behavior with respect to important suppliers might be more pronounced for the ones located further away. Distant suppliers are less likely to be part of a local production network, thus their clients are more likely to have a transactional relationship and low switching costs. As such, we 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 driven by 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 that are further away.

3.7. Discussion: Indirect Costs of Financial Distress

The coefficients estimated in Table 4 suggest that shocks to real estate prices can lead to a baseline 13% reduction in sales of distressed firms, and to larger reductions for firms with low market share, standardized products, or selling durable goods. This average effect would depend on how much of the reduction in sales represents a drop in quantities versus a drop in prices, as well as the supplier's fixed and variable cost structure, which for simplicity we assume to be proportional. Is this effect large enough to help explain the seemingly low leverage observed among public firms? The literature covering the tradeoff theory of debt highlights the importance of considering both direct costs of financial distress (e.g., bankruptcy costs) but also indirect costs of financial distress (e.g., Titman and Tsyplakov, 2007; Korteweg, 2010; Elkamhi, Ericsson, and Parsons, 2012).

To answer this question, we do a simple back-of-the-envelope calculation in the spirit of Almeida and Philippon (2007). Figure 2 illustrates these calculations. Each period, a firm can have high leverage and high real estate holdings with probability p_t , and there can be a negative shock to real estate prices with probability q_t . Each period, firms that suffer a shock to real estate prices will suffer a loss in value of M . Considering a firm value to sales ratio of 1.47 (i.e., the median in our sample), our baseline estimate implies that $M = 0.196 (0.133 \times 1.47)$. For simplicity, we assume that (1) for every t , $p_t = p$ and $q_t = q$ and are i.i.d. random variables; (2) p is independent of q ; and (3) the discount rate is constant and equals r .

In Panel A of Figure 2, we assume no bankruptcy, so firms continue to operate each period independently of the shock in the previous period (i.e., distress induced by the shock does not lead to default). In this case, the expected value of the costs of distress at time t discounted to period 0 is $\frac{pq}{(1+r)^t} M$. Given the independence across periods assumption, the present value of all future costs of distress is the sum of these discounted values, and it equals the value of the perpetuity, $\frac{pq}{r} M$.

In Panel B, we assume that firms file for bankruptcy and cannot continue to operate following distress. In this case, the expected value of indirect costs of distress at time t is given by $(1 - pq)^{t-1} pM$. Solving for the sum of discounted expected cost of distress yields $\frac{pq}{r+pq} M$.

Some firms will be able to continue operating after suffering distress due to real estate shocks, and others will not. Therefore, the costs of distress in the first case provide an upper bound of the total indirect costs of distress, and the costs in the second case provide a lower bound.

Table 10 contains estimates of indirect costs of financial distress considering different values of the parameters p , q , M , and r . In our baseline estimate, we assume that: $p = 0.125$, the product of the fraction of high leverage firms (0.5) by the fraction of high real estate assets firms (0.25); and $p = 0.100$, the fraction of counties that suffer a drop in real estate prices in a normal year such as 2011, $M = 0.196$, and $r = 6.7\%$ as in Almeida and Philippon (2007). Our baseline estimate of the present value of the expected indirect costs of financial distress is between 3.1% and 3.6% of total firm value.

The table also presents estimates of the indirect costs of financial distress for alternative scenarios using different values of the parameters. We find that the indirect costs of financial distress are larger in economic downturns, during a real estate crisis, and for firms with lower market share or selling durable and standardized goods. These costs are additional to the direct costs of bankruptcy calculated by Almeida and Philippon (2007) and Elkamhi et al. (2012), which range from 1% to 6% of firm value. Elkamhi et al. (2012) argue that modest indirect costs of financial distress in the range of 1% to 2% are sufficient to offset tax benefits (e.g., Graham, 2000).²⁴ We conclude that the indirect costs of financial distress triggered by real estate shocks are sizable and can help explain the capital structure puzzle in light of the tradeoff theory (see Titman and Tsyplakov, 2007; Korteweg, 2010; Elkamhi, Ericsson, and Parsons, 2012).

3.8. Who Initiates the Drop in Business Transactions?

Our identification strategy relies on comparing the same client buying from different suppliers each year. However, it is not clear, at the pair level, whether this reduction is client or supplier initiated. At the client-supplier pair level, it is challenging to determine who and what initiates the

²⁴ Almeida and Philippon (2007) estimates might include some costs of financial distress that occur before the default event, but they only focus on default events.

drop in business transactions. To add to this complexity, the channels are not mutually exclusive. It could be that clients observe financial distress increasing and decide to buy less from the distressed supplier. It could also be the case that clients observe economic distress (triggered by financial distress) and decide to buy less. In addition, it could be that suppliers are not able to supply their goods. However, the evidence so far is mostly consistent with the former explanation. We find that the reduction is more pronounced in more competitive (supplier) industries, manufacturing, durable goods, and for producers of less-specific goods, which is consistent with clients reducing their purchases from distressed suppliers. To further investigate this question, we exploit both multi-segment firms and firms' investment in working capital and fixed assets below.

3.8.1. Multi-Segment Firms

Multi-segment firms provide a good laboratory to analyze whether business transactions are client- or supplier-initiated as the level of financial distress is likely to be constant across divisions of the same supplier. If the reduction is client-initiated, we expect durable goods business segments to be relatively more affected than non-durable goods business segments. By contrast, if the reduction is supplier initiated, the effects are expected to be more homogeneous across business segments. To analyze this issue, we obtain a sample of distressed multi-segment suppliers with high real estate assets and high leverage that suffer a negative real estate shock in the 2000-2015 period; the unit of observation is a segment-year. The data are from the Compustat Segments file. The dependent variable is the sales of each segment in each year. The main explanatory variable is a dummy variable (*Durable Goods Segment*), which takes a value of one if the segment produces a durable good, and is zero otherwise. In Table 11, we show that the reduction in sales is more pronounced for durable goods segments than non-durable goods segments across all specifications. These results suggest that the indirect costs of financial distress are largely driven by clients reducing their exposure to distressed suppliers.

3.8.2. Investment and Financial Constraints

We next test the prediction that financially distressed suppliers suffer a reduction in sales because they cannot invest in working capital and fixed capital. Distressed suppliers in industries that extend more trade credit should face a larger decline if financial constraints hamper their ability to extend credit to their clients. We analyze this issue by estimating equation (1) separately for groups of suppliers with lower and higher than median values in the distribution of working capital (receivables and inventory) and investment.

In Table 12, columns (1) and (2) present results for the sample firms split into low and high trade credit provision in the firm's industry according to the median value of the distribution of the average ratio of accounts receivable to sales by industry. We find that the triple interaction coefficient is similar in both groups, although the coefficient is more precisely estimated in the low receivable group. Columns (3) and (4) present results for the sample firms split into low and high inventory in the firm's industry according to the median value of the distribution of the average ratio of inventory to cost of goods sold by industry. We find that the triple interaction coefficient is similar in magnitude in both groups, although the coefficient is more precisely estimated in the high inventory group. This result supports the notion that clients reduce their purchases from a distressed supplier. If, instead, suppliers cut back production, we would expect to see a stronger effect in the sales of the low inventory group than in the high inventory group. The high inventory group could use inventory to maintain its ability to supply its products with the same quality. We conclude that the working capital channel does not seem to explain our results.

Columns (5) and (6) present results for the sample firms split into low and high intensity of investment according to the median value of the distribution of the average ratio of capital expenditures to sales (*CAPEX*) by industry. We find that the triple interaction coefficient is not statistically different between the two groups, although the coefficient is slightly larger in the high *CAPEX* group. Thus, the investment channel does not seem to explain our results.²⁵

²⁵ In a related analysis, Table IA.8 in the Internet Appendix shows that the ratio of inventory to cost of goods sold does not decline for financially distressed suppliers that suffer a real estate shock. This result is consistent with the

4. Extensions and Robustness

4.1. Alternative Measures of Financial Constraints

Our main measure of financial constraints is book leverage. In Table IA.9 in the Internet Appendix, we consider alternative measures of financial constraints of the supplier. In the regression for column (1), *Market Leverage* corresponds to a dummy variable containing a one for firms with higher than median market leverage (the ratio of total debt to the market value of assets). In the regression for column (2), we consider the Kaplan-Zingales (KZ) index as a summary measure of financial constraints (Kaplan and Zingales, 1997). In this case, *Leverage* corresponds to firms with a KZ index above the median. In the regression for column (3), we consider a market-based measure of financial constraints, the *Distance to Default*, based on Merton's (1974) bond pricing model and estimated following the naïve approach proposed by Bharath and Shumway (2008). *Leverage* corresponds to firms with distance to default below the median. The coefficients in columns (1)-(3) are qualitatively similar to those in Table 4.

In the regression for column (4) of Table IA.9, we consider the continuous ratio of debt to assets (standardized to have a mean of zero and a standard deviation of one, to ease the economic interpretation of the results) as our measure of *Leverage*. Consistent with prior results, the estimated coefficient suggests that a one standard deviation increase in leverage leads to a 9.4% larger reduction in the sales of distressed firms. In the regression for column (5), we consider the ratio of short-term debt to total assets (standardized as before), as our measure of *Leverage*. This measure accounts for the fact that financial distress could be severe if the supplier relies more on short-term debt financing (i.e., financing with maturity of less than one year), as opposed to long-term debt. The point estimate of the triple interaction coefficient is slightly larger to the one in column (4). Last, column (6) of Table IA.9 shows the results using continuous measures of *Leverage*, *RE*, and ΔHP (all standardized to have a mean of zero and a standard deviation of one).

interpretation that the reduction in transactions is client initiated. If this reduction were supplier initiated, we would expect to see a decline in inventory as suppliers cut back production.

The estimate of the coefficient of the triple interaction is 0.034, and is statistically significant. The results in Table IA.9 show that overall our findings are consistent across different measures of financial constraints.

4.2. Extensive Margin

Our baseline results in Table 4 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 triple interaction, $High\ Leverage \times High\ RE \times \Delta HP < 0$, using a linear probability model. Table IA.10 in the Internet Appendix presents the results. 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 after a real estate shock is about 5 to 10 percentage points higher for a supplier with high exposure versus a supplier with low exposure. 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.²⁶

4.3. Robustness and Extensions

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

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 and the 2007-2011 real estate crisis. We estimate our baseline specifications for these periods and present the results

²⁶ 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.

in Table IA.11. We find that the coefficients of the triple interaction are negative and significant, and more pronounced during these periods.

A first concern regards the generalizability of our results. In particular, we analyze whether the segment sales data are representative of the total sales of the supplier firm. 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.12 reports the results, which are consistent with our baseline results.

Another generalizability concern related to the selected nature of the segments data is that financially distressed suppliers may be selling less to clients that we observe in our sample (those presenting more than 10% of total sales) but more to other clients that we do not observe. To address this concern, we estimate firm-level (rather than client-supplier level) regressions similar to those for Table 4 using the change in total sales as a dependent variable. Table IA.13 reports the results for the full sample of Compustat firms. The triple interaction coefficient remains negative and significant for most of these firm-level regressions.

We next address the concern that the choice of leverage and real estate assets are endogenous, which may compromise our identification strategy. We restrict our sample to firms with high leverage and high real estate assets, thus we are just exploiting the variation in real estate prices. Table IA.14 shows a significant reduction in sales following a drop in house prices. Although this approach is more limited in terms of the external validity of the results, it improves on the internal validity of our estimates.

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. We assume 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. Column (1) in Table IA.15 reports the results. The results are consistent with our baseline results in Table 4 as the coefficient of the triple interaction is negative and significant. The magnitude of the coefficient is -22%. This is consistent with the notion that our baseline estimates suffer from attenuation bias. In column (2), 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 each state. The results are also consistent with our baseline estimates. In Table IA.16, we restrict the sample to suppliers that operate in a single business segment. For these non-diversified suppliers, real estate assets are more likely to be located in the county of the headquarters. The estimated coefficient is -23%.

In our main tests, we use county-level house prices. As an alternative, we use MSA-level prices. Table IA.17 reports the results. We find that the magnitude of the triple interaction coefficient is larger than in Table 4, and equals -21%.

Table IA.18 reports the results when we exclude the sample industries with high exposure to real estate shocks based on the RE variable. In the regressions in columns (1)-(5), we exclude energy, utilities, telecoms, shops, and manufacturing, respectively. The results are consistent with our baseline results in Table 4 with point estimates between -14% and -10.8%.

Our baseline results include real estate assets reported as a firm's fixed assets in the balance sheet. However, some of these assets may be leased, not owned. 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.19 shows the results. Consistent with the notion that leased assets cannot be used as collateral, the estimated coefficients are larger than our baseline estimates.

5. Conclusion

We estimate the indirect costs of financial distress due to lost sales 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, as well as 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 13% following a reduction in local real estate prices. 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 each year.

The indirect costs of financial distress are more pronounced in more competitive industries, manufacturing and durable goods industries, and for producers of less-specific goods. In addition, we find that durable goods sales decline more than non-durable sales in distressed multi-segment firms. These results suggest that the indirect costs of financial distress are driven by clients reducing purchases from distressed suppliers, rather than by suppliers cutting back their supply of products and/or services.

The costs of financial distress are an important deviation from the Modigliani and Miller (1958) framework with no frictions. We provide evidence that the indirect costs of financial distress are sizable and thus should be an important consideration of capital structure decisions. Our baseline estimate of the expected indirect costs of distress lies between 3.1% and 3.6% of total firm value, in present value terms, and can go up to 20% in a downturn. These costs are additional to the direct costs of default, and only consider real estate shocks as a trigger of financial distress. As a benchmark in the literature, Elkamhi et al. (2012) show that modest indirect costs of financial distress in the range of 1-2% are sufficient to offset tax benefits. Korteweg (2010) estimates costs of financial distress, including direct and indirect ones to be in the range of 15% to 30% for firms in or near bankruptcy. We conclude that the indirect costs of financial distress are significant and can help explain the capital structure puzzle.

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Table 1: Summary Statistics

The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Panels A and B present mean, median, standard deviation, 5th percentile, 95th percentile, and number of observations for each supplier and client variable. Variable definitions are in Table A.1 in the Appendix.

Panel A: Supplier Variables

	Mean	Median	Std. Dev.	5th Percentile	95th Percentile	Number of Suppliers	Num. of Obs.
$\Delta \log(\text{Sales})$	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
$\Delta \text{HP} < 0$	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
Adjusted RE	0.153	0.093	0.188	0.003	1.000	4,678	6,809
High Adjusted RE	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 B: Client Variables

	Mean	Median	Std. Dev.	5th Percentile	95th Percentile	Number of Clients	Num. of Obs.
$\Delta \log(\text{Sales})$	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
$\Delta \text{HP} < 0$	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 2: Sample Balance Tests

In this table, we compare the characteristics of high leverage and high real estate assets firms located in counties that suffered a real estate shock $\Delta HP < 0$ (treatment group) with high leverage and high real estate assets firms located in counties that did not suffer a real estate shock $\Delta HP \geq 0$ (control group). The normalized difference is $\Delta_x = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{S_t^2 + S_c^2}}$,

where $\bar{X}_t, \bar{X}_c$ are the sample means and S_t^2, S_c^2 are the sample variances of variable X for the treatment and control groups, respectively. The sample in Panel A consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The sample in Panel B consists of yearly observations of Compustat firms in the 2000-2015 period. Variable definitions are in Table A.1 in the Appendix.

Panel A: Supplier-Client Sample

	$\Delta HP \geq 0$ (Observations = 1,488)		$\Delta HP < 0$ (Observations = 409)		Difference in mean t -statistic	Normalized difference in mean
	Mean	Standard Deviation	Mean	Standard Deviation		
Leverage	0.460	0.273	0.453	0.202	0.564	0.020
RE	0.576	0.192	0.570	0.180	0.618	0.024
ΔHP	5.737	4.783	-4.121	4.508	38.649	1.500
HP	4.056	1.620	5.271	2.599	-8.983	-0.396
Tobin's q	1.484	1.062	1.339	0.590	3.610	0.119
Cash	0.052	0.081	0.057	0.058	-1.594	-0.057
Assets (log)	6.554	1.791	6.959	1.494	-4.632	-0.173

Panel B: Firm-Level Sample

	$\Delta HP \geq 0$ (Observations = 9,510)		$\Delta HP < 0$ (Observations = 2,798)		Difference in mean t -statistic	Normalized difference in mean
	Mean	Standard Deviation	Mean	Standard Deviation		
Leverage	0.568	0.535	0.552	0.494	1.453	0.022
RE	0.598	0.178	0.600	0.173	-0.532	-0.008
ΔHP	6.639	5.298	-4.743	5.242	100.717	1.527
HP	4.227	1.956	5.467	2.639	-23.066	-0.378
Tobin's q	3.618	10.082	3.367	9.423	1.219	0.018
Cash	0.051	0.074	0.058	0.076	-4.700	-0.072
Assets (log)	5.802	2.973	6.342	2.891	-8.637	-0.130

Table 3: Relevance Condition

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. The dependent variable in the regression for column (1) is $\Delta Distance\ to\ Default$, the change in the distance to default between years t and $t+1$. The dependent variable in the regression for column (2) is *Covenant Violation*, a dummy variable that takes a value of one if the firm violated at least one debt covenant between years t and $t+1$, and zero otherwise. The dependent variable in the regression for column (3) is *Doubts of Going Concern*, a dummy variable that takes a value of one equal to one if the auditor expressed doubts of the viability of the firm as a going concern between years t and $t+1$, and zero otherwise. *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 third quartile, and zero otherwise. $\Delta HPI < 0$ is a dummy variable that takes a value of one if the change between years $t-1$ and t in the house price index (*HPI*) of the county where the supplier is located is negative, and zero otherwise. Control variables are measured in year $t-1$. Percentiles are calculated using the population of Compustat firms. Variable definitions are in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Robust p -values clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta Distance\ to\ Default$ (1)	Covenant Violation (2)	Doubts of Going Concern (3)
High Leverage $\times$ High RE $\times$ $\Delta HPI < 0$	-0.644*** (0.001)	0.031* (0.060)	0.020* (0.091)
High Leverage	0.268*** (0.000)	0.049*** (0.000)	0.101*** (0.000)
High RE	-0.096 (0.212)	0.010 (0.151)	0.005 (0.449)
$\Delta HPI < 0$	-0.206** (0.045)	0.017*** (0.000)	0.017*** (0.001)
High Leverage $\times$ High RE	0.011 (0.906)	-0.003 (0.724)	-0.066*** (0.000)
High Leverage $\times$ $\Delta HPI < 0$	0.392*** (0.000)	-0.044*** (0.000)	-0.018** (0.022)
High RE $\times$ $\Delta HPI < 0$	0.498*** (0.002)	-0.002 (0.825)	0.001 (0.859)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	48,960	44,950	59,113
R-squared	0.086	0.039	0.065

Table 4: Baseline Results

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales from supplier i to client j between years $t-1$ and t . *Leverage* is the debt to assets ratio. *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 third quartile, and zero otherwise. In the regressions for columns (1), (2), and (3), ΔHP 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 the regression for column (4), ΔHP is a dummy variable that takes a value of one if the change between years $t-1$ and t in *HP* is lower than the 10th percentile (-3.3%), and zero otherwise. In the regression for column (5), ΔHP is the continuous change in real estate prices. In column (6), ΔHP is a dummy variable that takes a value of one if the change between years $t-2$ and $t-1$ in *HP* is negative, and zero otherwise. The regression for column (3) includes controls for lagged values of *Tobin's q*, *Cash*, *Assets* (log), and *HP*. Variable definitions are in Table A.1 in the Appendix. Percentiles are calculated using the population of Compustat firms. 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)
	$\Delta HP < 0$	$\Delta HP < 0$	$\Delta HP < 0$	$\Delta HP < -3.3\%$	ΔHP	$\Delta HP_{t-2 \rightarrow t-1} < 0$
High Leverage $\times$ High RE $\times$ ΔHP	-0.104** (0.025)	-0.133** (0.032)	-0.119* (0.072)	-0.136* (0.096)	0.010** (0.038)	-0.114* (0.067)
High Leverage	0.004 (0.789)	-0.001 (0.956)	-0.006 (0.765)	-0.004 (0.808)	0.009 (0.599)	0.005 (0.785)
High RE	-0.024 (0.249)	-0.055* (0.062)	-0.041 (0.176)	-0.044* (0.097)	-0.009 (0.724)	-0.051* (0.089)
ΔHP	-0.009 (0.709)	-0.011 (0.736)	-0.019 (0.588)	-0.037 (0.242)	0.001 (0.739)	-0.012 (0.709)
High Leverage $\times$ High RE	0.030 (0.244)	0.050 (0.145)	0.050 (0.174)	0.033 (0.284)	-0.019 (0.536)	0.041 (0.231)
High Leverage $\times$ ΔHP	0.014 (0.558)	0.010 (0.763)	0.001 (0.974)	0.037 (0.376)	-0.002 (0.382)	-0.009 (0.781)
High RE $\times$ ΔHP	0.067* (0.066)	0.093* (0.075)	0.100* (0.069)	0.096 (0.112)	-0.006* (0.099)	0.088* (0.095)
Supplier Controls	No	No	Yes	No	No	No
Client $\times$ Year FE	Yes	No	No	No	No	No
Supp. Industry $\times$ Client $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Observations	15,214	10,877	9,012	10,877	10,877	10,896
R-squared	0.286	0.353	0.366	0.353	0.353	0.352

Table 5: Alternative Measures of Real Estate Assets

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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. $\Delta \text{HP} < 0$ 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 column (1), *High RE* is a dummy variable that takes a value of one if *Market RE* is above the median, 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 column (2), *High RE* is a dummy variable taking the value of one if *Commercial RE* is above the median, 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. In column (3), *High RE* is a dummy variable that takes a value of one if *Adjusted RE* is above the third quartile, and zero otherwise. *Adjusted RE* 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 column (4), *High RE* is a dummy variable that takes a value of one if *Industry RE* is above the third quartile, zero otherwise. *Industry RE* is 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. 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) Market RE	(2) Commercial RE	(3) Adjusted RE	(4) Industry RE
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.148* (0.081)	-0.124* (0.073)	-0.279*** (0.006)	-0.167* (0.060)
High Leverage	-0.099** (0.019)	-0.004 (0.940)	0.002 (0.914)	0.000 (0.998)
High RE	-0.141*** (0.008)	-0.040 (0.400)	-0.037 (0.415)	-0.094** (0.021)
$\Delta \text{HP} < 0$	-0.034 (0.397)	0.046 (0.344)	0.018 (0.625)	-0.010 (0.737)
High Leverage $\times$ High RE	0.140** (0.033)	0.028 (0.673)	0.100* (0.056)	0.081** (0.048)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.036 (0.417)	0.027 (0.625)	-0.011 (0.758)	0.000 (0.990)
High RE $\times$ $\Delta \text{HP} < 0$	0.139* (0.060)	0.148*** (0.006)	0.146* (0.074)	0.160* (0.056)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	943	950	4,496	10,877
R-squared	0.417	0.451	0.408	0.353

Table 6: Local Economic Conditions

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. In column (1), the sample is restricted to suppliers located in counties with high land supply elasticity (i.e., elasticity above one). In column 2, 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. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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) High Supply Elasticity	(2) Small Suppliers in Large Counties
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.118* (0.054)	-0.189** (0.013)
High Leverage	0.009 (0.816)	-0.001 (0.962)
High RE	-0.010 (0.659)	-0.068** (0.042)
$\Delta \text{HP} < 0$	-0.043 (0.147)	-0.031 (0.395)
High Leverage $\times$ High RE	0.054 (0.122)	0.064 (0.113)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.074 (0.178)	0.004 (0.916)
High RE $\times$ $\Delta \text{HP} < 0$	0.030 (0.474)	0.108* (0.081)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
Observations	5,686	8,782
R-squared	0.423	0.359

Table 7: 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 sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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. 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 $\times$ High RE $\times$ $\Delta HP < 0$	-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)
$\Delta HP < 0$	-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 $\times$ 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 $\times$ $\Delta HP < 0$	-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 $\times$ $\Delta HP < 0$	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 $\times$ Client $\times$ 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 8: Durable Goods and Manufacturing

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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 $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.149** (0.036)	0.006 (0.933)	-0.111* (0.092)	-0.497*** (0.000)
High Leverage	0.004 (0.865)	-0.031 (0.267)	0.002 (0.934)	-0.024 (0.546)
High RE	-0.053 (0.107)	-0.048 (0.320)	-0.065** (0.046)	-0.008 (0.855)
$\Delta \text{HP} < 0$	-0.009 (0.814)	-0.018 (0.641)	-0.006 (0.866)	-0.127* (0.054)
High Leverage $\times$ High RE	0.054 (0.162)	0.002 (0.967)	0.049 (0.189)	0.070 (0.231)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.008 (0.846)	0.012 (0.808)	-0.001 (0.974)	0.176** (0.040)
High RE $\times$ $\Delta \text{HP} < 0$	0.093 (0.121)	0.043 (0.489)	0.087 (0.117)	0.325** (0.011)
Supplier Industry $\times$ Client $\times$ 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 9: Specificity in Supplier Product Market

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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 $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.255** (0.011)	-0.044 (0.604)	-0.175* (0.074)	-0.040 (0.844)	-0.388* (0.100)	-0.009 (0.892)
High Leverage	-0.052** (0.039)	0.023 (0.369)	0.000 (0.997)	0.077* (0.087)	-0.012 (0.902)	0.012 (0.538)
High RE	-0.084* (0.055)	-0.028 (0.527)	-0.080** (0.044)	0.099 (0.219)	-0.032 (0.748)	-0.021 (0.492)
$\Delta \text{HP} < 0$	-0.047 (0.363)	-0.003 (0.944)	-0.061 (0.281)	0.038 (0.580)	-0.109 (0.343)	0.012 (0.711)
High Leverage $\times$ High RE	0.126*** (0.006)	0.002 (0.979)	0.048 (0.300)	-0.091 (0.348)	0.111 (0.348)	-0.016 (0.659)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.095 (0.103)	-0.027 (0.510)	0.068 (0.246)	-0.058 (0.482)	0.153 (0.443)	-0.026 (0.388)
High RE $\times$ $\Delta \text{HP} < 0$	0.217** (0.018)	0.008 (0.902)	0.147* (0.053)	0.018 (0.895)	0.332** (0.033)	0.008 (0.883)
Supplier Industry $\times$ Client $\times$ 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 10: Present Value of Indirect Costs of Financial Distress

This table contains back-of-the-envelope estimates of the present value of the indirect costs of financial distress implied by our estimates. p is the probability that a firm is highly levered and has high real estate holdings. q is the probability of a real estate shock. r is the discount rate. β is the estimated coefficient of the effect of financial distress on supplier sales. v is the firm value to sales ratio (for more details, refer to the description in Section 3.7 and to Figure 2). The last two columns show the estimates of the present value of the expected indirect costs of financial distress (PV) under two cases: the firm cannot operate after financial distress (no continuation after distress), and the firm can continue to operate following distress (continuation after distress).

	p	q	r	β	v	$M = \beta v$	PV (no continuation after distress)	PV (continuation after distress)
Baseline	0.125	0.100	0.067	0.133	1.470	0.196	0.031	0.036
Low Interest Rate	0.125	0.100	0.020	0.133	1.470	0.196	0.075	0.122
RE Crisis	0.125	0.900	0.067	0.133	1.470	0.196	0.123	0.328
Downturn	0.500	0.200	0.067	0.133	1.470	0.196	0.117	0.292
Low Market Share	0.125	0.100	0.067	0.218	1.470	0.320	0.050	0.060
Durable Goods	0.125	0.100	0.067	0.149	1.470	0.219	0.034	0.041
Low R&D	0.125	0.100	0.067	0.255	1.470	0.375	0.059	0.070
Distressed	0.800	0.100	0.067	0.133	1.470	0.196	0.106	0.233

Table 11: Sales of Multi-Segment Distressed Firms

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-segment level. The sample consists of yearly observations of Compustat Segments in the 2000-2015 period that satisfy the following criteria (distressed multi-segment suppliers): (i) the ratio of total debt to total assets is above the median; (ii) the ratio of PPE to total assets is above the third quartile; and (iii) the change between years $t-1$ and t in the house price index (HP) of the county where the firm is located is negative. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales of a business segment between years $t-1$ and t . *Durable Goods Segment* is a dummy variable that takes a value one if the primary or secondary SIC code of the segment corresponds to durable goods (based on the Fama-French industry classification), and zero otherwise. 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)
Durable Goods Segment	-0.188*** (0.000)	-0.182*** (0.000)	-0.213** (0.035)
HP		0.003 (0.320)	
Tobin's q		-0.001 (0.421)	
Cash		0.062 (0.373)	
Assets (log)		-0.001 (0.827)	
Year FE	Yes	Yes	No
Firm $\times$ Year FE	No	No	Yes
Observations	7,239	5,633	5,337
R-squared	0.020	0.023	0.042

Table 12: Investment in Working Capital and Fixed Assets

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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 receivable groups consist of those suppliers in industries (three-digit SIC) with average ratio of accounts receivable to total assets below and above the median. In columns (3) and (4), the low and high inventory groups consist of those suppliers in industries (three-digit SIC) with average ratio of inventory to cost of goods sold below and above the median. In columns (5) and (6), the low and high CAPEX groups consist of those suppliers in industries (three-digit SIC) with average ratio of capital expenditures to property, plant, and equipment (PPE) below and above 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.

	Receivable		Inventory		CAPEX	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage $\times$ High RE $\times$ $\Delta HP < 0$	-0.124** (0.021)	-0.140 (0.280)	-0.138 (0.228)	-0.129* (0.063)	-0.103* (0.085)	-0.171* (0.079)
High Leverage	-0.011 (0.563)	0.007 (0.875)	-0.038 (0.381)	0.003 (0.894)	-0.018 (0.457)	0.008 (0.773)
High RE	-0.056* (0.091)	-0.092 (0.134)	-0.047 (0.386)	-0.057 (0.135)	-0.038 (0.213)	-0.070 (0.104)
$\Delta HP < 0$	-0.029 (0.308)	0.013 (0.846)	0.016 (0.799)	-0.017 (0.643)	-0.023 (0.491)	-0.013 (0.753)
High Leverage $\times$ High RE	0.046 (0.225)	0.077 (0.249)	0.085 (0.162)	0.052 (0.268)	0.018 (0.632)	0.077 (0.127)
High Leverage $\times$ $\Delta HP < 0$	0.009 (0.763)	-0.003 (0.964)	0.032 (0.664)	0.008 (0.837)	0.019 (0.637)	0.010 (0.819)
High RE $\times$ $\Delta HP < 0$	0.078 (0.103)	0.143 (0.166)	0.108 (0.265)	0.058 (0.299)	0.086* (0.072)	0.106 (0.187)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,313	4,189	3,071	7,568	2,937	7,495
R-squared	0.409	0.312	0.404	0.335	0.394	0.349

Figure 1: Placebo Regressions

This figure shows the coefficient and 90% confidence intervals of the triple interaction, $High\ Leverage \times High\ RE \times \Delta HP < 0$, in ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is $\Delta \log(Sales)$, defined as the change in the log of sales from supplier i to client j between years $t+k-1$ and $t+k$ ($k = -3, -2, \dots, +3$). 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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. The plotted coefficients correspond to the same regression specification as the one in column (2) of Table 4. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period.

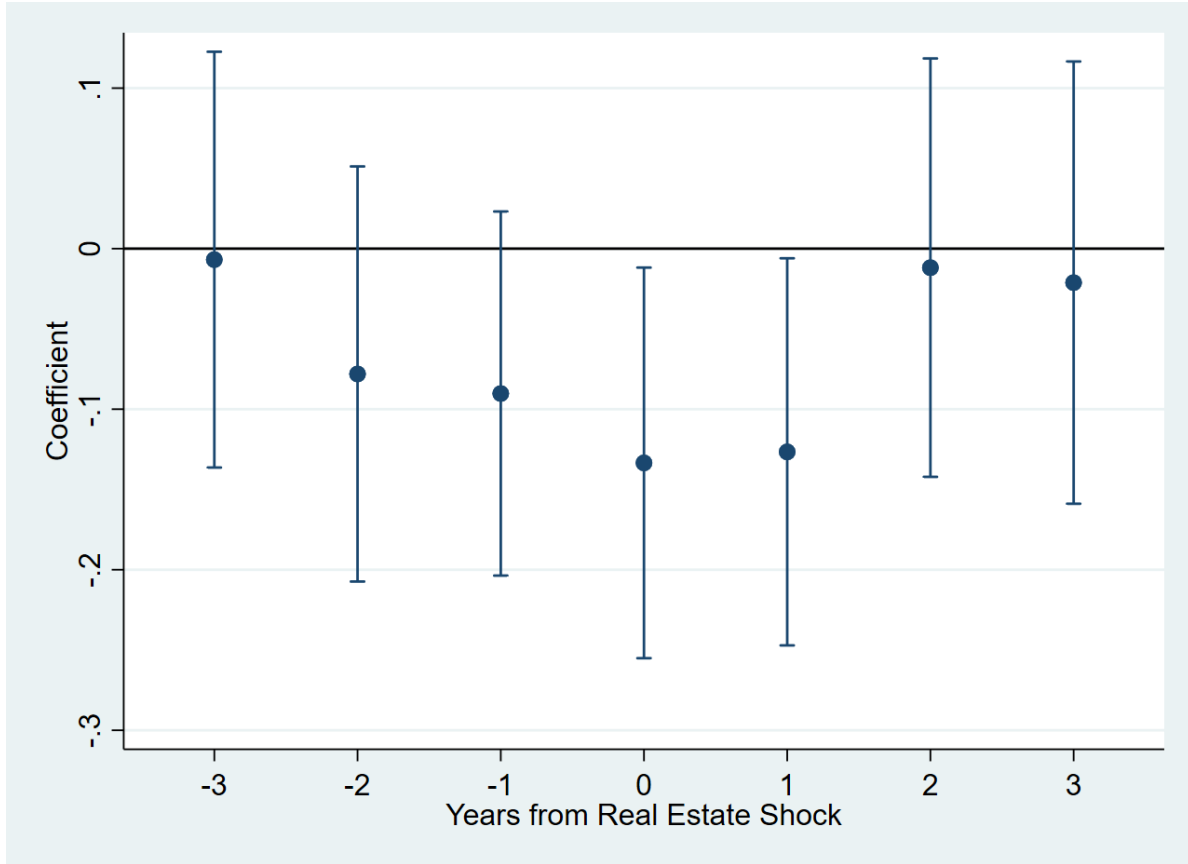
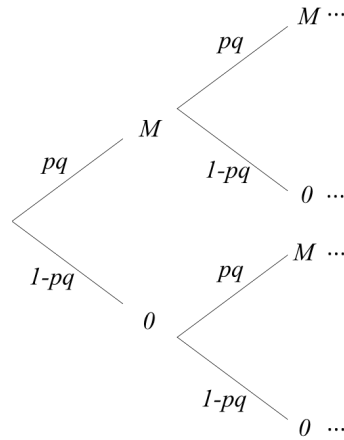


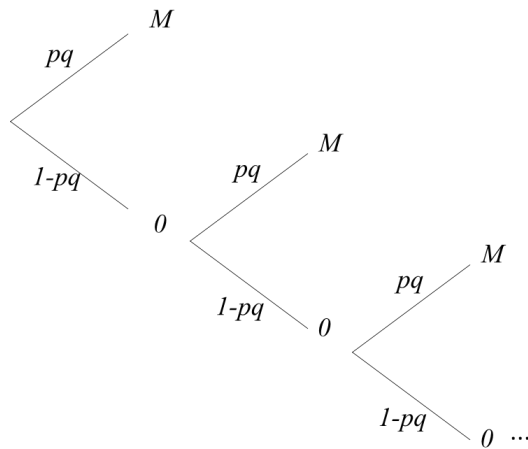
Figure 2: Model for the Indirect Costs of Financial Distress

This figure illustrates a simple model of the indirect costs of financial distress implied by our estimates. Each period, a firm can be highly levered and have high real estate holdings with probability p , and there can be a shock to real estate prices with probability q , with p and q i.i.d random variables that are independent of each other. Firms that suffer a shock to real estate prices have a loss in value of M . The discount rate is constant and equals r . The expected costs of distress are estimated under two scenarios: the firm cannot operate after financial distress (Panel A), and the firm can continue to operate following distress (Panel B).

Panel A: Firms Continue to Operate After Distress



Panel B: Firms Do Not Continue to Operate After Financial Distress



Appendix

Table A.1: Variable Definitions

Variable	Definition
$\Delta \log(\text{Sales})$	Change in the log of sales from supplier i to client j between years $t-1$ and t (Compustat).
$\Delta \text{Distance to Default}$	Change in the distance to default measure of Merton's (1974) bond pricing model estimated following the naïve approach proposed by Bharath and Shumway (2008) between years t and $t+1$.
Covenant Violation	Dummy variable that takes a value of one if the firm violated at least one debt covenant between years t and $t+1$, and zero otherwise. Covenant violations registered with the SEC are taken from Amir Sufi's publicly available data set at https://amirsufi.net/data.html .
Doubts of Going Concern	Dummy variable that takes a value of one equal to one if the auditor expressed doubts of the viability of the firm as a going concern between years t and $t+1$, and zero otherwise (Capital IQ).
Leverage	Total debt, defined as debt in current liabilities plus long-term debt, divided by total assets (Compustat $(\text{DLC} + \text{DLTT}) / \text{AT}$).
High Leverage	Dummy variable that takes a value of one if Leverage is above the median of the Compustat sample, 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.
$\Delta \text{HP} < 0$	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 third quartile of the Compustat sample, 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 of the Compustat sample, and zero otherwise.
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 $\text{AT} + \text{CSHO} \times \text{PRCC}_F - [\text{AT} - (\text{LT} + \text{PSTKL}) + \text{TXDITC}] / \text{AT}$).
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 .

Variable	Definition
Non-Durable Goods Industry	Dummy variable that takes a value of one if the SIC code of the firm corresponds to non-durable goods (based on the Fama-French industry classification), and zero otherwise.
Manufacturing Industry	Dummy variable that takes a value of one if the SIC code of the firm corresponds to manufacturing (based on the Fama-French industry classification), and zero otherwise.
Durable Goods Segment	Dummy variable that takes a value of one if the primary or secondary SIC code of the segment corresponds to durable goods (based on the Fama-French industry classification), and zero otherwise.
Receivable	Accounts receivable divided by sales (Compustat RECT/SALE).
Inventory	Inventory divided by cost of goods sold (Compustat INVT/COGS).
CAPEX	Capital expenditures divided by property, plant and equipment (PPE) (Compustat CAPX/PPENT).

Internet Appendix for
“Indirect Costs of Financial Distress”

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Table IA.1: Sample Description

This table 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. The last two columns contain 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 .

Year	Number of Observations	Number of Suppliers	Number of Clients	Average Number of Suppliers per Client	Average Supplier Sales Coverage	Average ΔHP	Fraction $\Delta HP < 0$
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 IA.2: Industry Fixed Effects using Three-Digit SIC Codes

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.132* (0.067)
High Leverage	0.001 (0.978)
High RE	-0.069** (0.046)
$\Delta \text{HP} < 0$	0.009 (0.813)
High Leverage $\times$ High RE	0.075* (0.061)
High Leverage $\times$ $\Delta \text{HP} < 0$	-0.012 (0.753)
High RE $\times$ $\Delta \text{HP} < 0$	0.088 (0.137)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	9,113
R-squared	0.359

Table IA.3: Alternative Clustering of Standard Errors

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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 column (1), standard errors are clustered at the county level. In column (2), standard errors are double clustered at the supplier and client level. Robust p-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Cluster by County	(2) Cluster by Supplier and Client
High Leverage $\times$ High RE $\times$ $\Delta HP < 0$	-0.133** (0.033)	-0.133** (0.015)
High Leverage	-0.001 (0.950)	-0.001 (0.955)
High RE	-0.055* (0.078)	-0.055** (0.026)
$\Delta HP < 0$	-0.011 (0.747)	-0.011 (0.749)
High Leverage $\times$ High RE	0.050 (0.142)	0.050 (0.124)
High Leverage $\times$ $\Delta HP < 0$	0.010 (0.709)	0.010 (0.728)
High RE $\times$ $\Delta HP < 0$	0.093* (0.066)	0.093* (0.056)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
Observations	10,877	10,877
R-squared	0.353	0.353

Table IA.4: Interactions with Control Variables

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. In column (2) we additionally control for the interaction of *High Leverage*, *High RE*, and $\Delta \text{HP} < 0$ with each firm-level control, *Tobin's q*, *Cash*, and log of *Assets* (coefficients not shown). 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 $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.119* (0.072)	-0.110* (0.095)
High Leverage	-0.007 (0.758)	0.058 (0.305)
High RE Exposure	-0.042 (0.162)	-0.072 (0.320)
$\Delta \text{HP} < 0$	-0.019 (0.586)	0.040 (0.553)
High Leverage $\times$ High RE	0.051 (0.158)	0.014 (0.707)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.001 (0.986)	-0.015 (0.699)
High RE $\times$ $\Delta \text{HP} < 0$	0.100* (0.070)	0.071 (0.193)
HP	0.001 (0.889)	-0.001 (0.948)
Tobin's q	0.017* (0.052)	0.024*** (0.007)
Cash	-0.066 (0.597)	0.006 (0.964)
Assets (log)	0.005 (0.565)	0.000 (0.980)
HP $\times$ Tobin's q	0.001 (0.613)	0.002 (0.208)
HP $\times$ Cash	-0.003 (0.847)	-0.007 (0.672)
HP $\times$ Assets (log)	0.001 (0.634)	0.001 (0.624)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
High Leverage, High RE and $\Delta \text{HP} < 0 \times$ Controls	No	Yes
Observations	9,012	9,012
R-squared	0.366	0.369

Table IA.5: Real Estate Prices, Exposure, and Supplier Sales

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales from supplier i to client j between years $t-1$ and t . *High RE* is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High RE $\times$ $\Delta \text{HP} < 0$	0.016 (0.659)
High RE	-0.025 (0.256)
$\Delta \text{HP} < 0$	-0.006 (0.819)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	10,921
R-squared	0.353

Table IA.6: Client-Supplier Location

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. Panel A includes supplier county $\times$ year fixed effects. 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.174** (0.044)
High Leverage	-0.013 (0.595)
High RE	-0.081** (0.048)
$\Delta \text{HP} < 0$	-0.073 (0.190)
High Leverage $\times$ High RE	0.081* (0.086)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.022 (0.611)
High RE $\times$ $\Delta \text{HP} < 0$	0.076 (0.297)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Supplier County $\times$ Year FE	Yes
Observations	9,527
R-squared	0.508

Table IA.6: continued

Panel B: Sample Split Based on Client-Supplier Distance

	Low (1)	High (2)
High Leverage $\times$ High RE $\times$ Δ HP<0	-0.067 (0.432)	-0.315** (0.020)
High Leverage	-0.002 (0.930)	-0.042 (0.146)
High RE	-0.039 (0.312)	-0.103* (0.091)
Δ HP<0	0.013 (0.780)	0.013 (0.778)
High Leverage $\times$ High RE	0.011 (0.825)	0.127* (0.086)
High Leverage $\times$ Δ HP<0	-0.007 (0.889)	0.034 (0.486)
High RE $\times$ Δ HP<0	0.062 (0.404)	0.184* (0.077)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
Observations	3,411	3,500
R-squared	0.415	0.386

Table IA.7: Client-Supplier Relationship

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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
	Weight	Weight	Weight	Weight	Weight	Weight
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	0.090 (0.546)	-0.188*** (0.003)	-0.140 (0.583)	-0.457** (0.047)	0.238 (0.221)	-0.097 (0.208)
High Leverage	0.037 (0.346)	-0.025 (0.239)	-0.023 (0.675)	-0.048 (0.161)	0.020 (0.746)	-0.005 (0.880)
High RE	0.007 (0.915)	-0.121*** (0.003)	-0.007 (0.951)	-0.238*** (0.003)	0.070 (0.371)	-0.048 (0.329)
$\Delta \text{HP} < 0$	0.033 (0.658)	0.037 (0.237)	0.127 (0.307)	0.059 (0.191)	0.078 (0.554)	0.007 (0.880)
High Leverage $\times$ High RE	-0.016 (0.840)	0.104** (0.019)	0.126 (0.408)	0.182* (0.052)	-0.173 (0.106)	0.046 (0.432)
High Leverage $\times$ $\Delta \text{HP} < 0$	-0.122 (0.186)	0.019 (0.529)	-0.059 (0.659)	0.031 (0.511)	-0.090 (0.460)	0.005 (0.928)
High RE $\times$ $\Delta \text{HP} < 0$	0.008 (0.932)	0.102* (0.065)	0.030 (0.864)	0.373* (0.074)	-0.114 (0.440)	0.044 (0.475)
Supplier Industry $\times$ Client $\times$ 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

Table IA.8: Change in Inventory

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. The dependent variable is the change in the ratio of inventory to the cost of goods sold 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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. Column (2) includes the same firm-level control variables as in column (3) of Table 4 (coefficients not shown). All control variables are lagged one period. Robust p -values clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
High Leverage $\times$ High RE $\times$ $\Delta HP < 0$	0.005 (0.325)	0.007 (0.201)
High Leverage	-0.005** (0.012)	-0.003 (0.179)
High RE	0.002 (0.414)	0.003 (0.171)
$\Delta HP < 0$	-0.003 (0.235)	-0.004 (0.147)
High Leverage $\times$ High RE	0.002 (0.370)	0.002 (0.530)
High Leverage $\times$ $\Delta HP < 0$	-0.002 (0.591)	-0.003 (0.469)
High RE $\times$ $\Delta HP < 0$	-0.001 (0.709)	-0.001 (0.758)
Controls	No	Yes
Industry $\times$ Year FE	Yes	Yes
Observations	71,809	59,742
R-squared	0.014	0.017

Table IA.9: Alternative Measures of Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales from supplier i to client j between years $t-1$ and t . The table considers different proxies of financial constraints (FC). In column (1), *Market 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 column (2), *Leverage* is a dummy variable that takes a value of one if the Kaplan-Zingales index is above the median, and zero otherwise. In column (3), *Leverage* is a dummy variable that takes a value of one if the distance to default is above the median, and zero otherwise. In column (4), *Continuous Leverage* is the ratio of total debt to total assets. In column (5), *Leverage* is the ratio of short-term debt to total assets. In column (6), *Leverage* is the ratio of total debt to total assets. In columns (1) to (5), RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the third quartile, and zero otherwise and ΔHP is a dummy variable that takes a value of one if the change between years $t-1$ and t in the house price index of the county where the supplier is located is negative, and zero otherwise. Robust p -values clustered at the supplier level are reported in parentheses. In column (6), RE is the ratio of PPE to total assets and ΔHP is the change between years $t-1$ and t in the house price index of the county where the supplier is located. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Market Leverage	(2) Kaplan- Zingales	(3) Distance to Default	(4) Continuous Leverage	(5) Short-term Debt	(6) Continuous Terms
$FC \times RE \times \Delta HP$	-0.158** (0.011)	-0.122* (0.074)	-0.126* (0.059)	-0.094* (0.055)	-0.112* (0.084)	0.034*** (0.002)
FC	-0.014 (0.489)	-0.011 (0.614)	-0.008 (0.713)	-0.002 (0.869)	0.001 (0.937)	-0.000 (1.000)
RE	-0.030 (0.300)	-0.005 (0.904)	-0.015 (0.608)	-0.038* (0.081)	-0.030 (0.150)	-0.022* (0.075)
ΔHP	-0.024 (0.451)	-0.016 (0.634)	0.003 (0.933)	-0.008 (0.766)	-0.012 (0.665)	-0.011 (0.315)
$FC \times RE$	0.024 (0.489)	-0.007 (0.870)	-0.022 (0.508)	0.034 (0.283)	0.034 (0.326)	0.010 (0.355)
$FC \times \Delta HP$	0.028 (0.378)	0.024 (0.578)	-0.002 (0.952)	0.003 (0.873)	-0.029 (0.360)	0.014 (0.142)
$RE \times \Delta HP$	0.109** (0.032)	0.104* (0.063)	0.106** (0.037)	0.040 (0.287)	0.019 (0.601)	-0.019 (0.101)
Supp. Ind. $\times$ Client $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,660	8,861	8,660	10,877	10,921	10,877
R-squared	0.360	0.362	0.368	0.353	0.354	0.355

Table IA.10: Extensive Margin

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. 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 ($\Delta HP < 0$) 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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. Column (3) includes the same firm-level control variables as in column (3) in Table 4 (coefficients not shown). 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)
High Leverage $\times$ High RE $\times$ $\Delta HP < 0$	0.084** (0.014)	0.055 (0.178)	0.097** (0.035)
High Leverage	0.024** (0.024)	0.021 (0.107)	0.044*** (0.002)
High RE	-0.014 (0.349)	-0.011 (0.588)	-0.003 (0.882)
$\Delta HP < 0$	0.019 (0.200)	-0.012 (0.501)	-0.007 (0.724)
High Leverage $\times$ High RE	0.009 (0.653)	0.007 (0.793)	-0.013 (0.627)
High Leverage $\times$ $\Delta HP < 0$	-0.056*** (0.001)	-0.038* (0.091)	-0.053** (0.029)
High RE $\times$ $\Delta HP < 0$	-0.049** (0.028)	-0.017 (0.555)	-0.036 (0.287)
Firm-Level Controls	No	No	Yes
Client $\times$ Year FE	Yes	No	No
Supplier Industry $\times$ Client $\times$ Year FE	No	Yes	Yes
Observations	18,243	12,792	10,686
R-squared	0.369	0.442	0.452

Table IA.11: Financial Crisis Period

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. In column 1, the sample consists of yearly observations of Compustat supplier-client pairs in the 2007-2009 period (Great Recession). In column 2, the sample consists of yearly observations of Compustat supplier-client pairs in the 2007-2011 period (Real Estate Crisis). The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta HP < 0$ 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. 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) Great Recession	(2) Real Estate Crisis
High Leverage $\times$ High RE $\times$ $\Delta HP < 0$	-0.293** (0.037)	-0.201* (0.082)
High Leverage	0.002 (0.975)	0.016 (0.803)
High RE	-0.133* (0.086)	-0.143* (0.088)
$\Delta HP < 0$	-0.046 (0.357)	-0.002 (0.972)
High Leverage $\times$ High RE	0.100 (0.294)	0.116 (0.229)
High Leverage $\times$ $\Delta HP < 0$	0.064 (0.438)	-0.004 (0.951)
High RE $\times$ $\Delta HP < 0$	0.247** (0.016)	0.175* (0.073)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
Observations	2,106	3,456
R-squared	0.338	0.339

Table IA.12: Sample with Sales Coverage Above 30%

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. 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. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.191** (0.045)
High Leverage	0.020 (0.475)
High RE	-0.061 (0.149)
$\Delta \text{HP} < 0$	-0.017 (0.721)
High Leverage $\times$ High RE	0.016 (0.742)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.005 (0.917)
High RE $\times$ $\Delta \text{HP} < 0$	0.101 (0.155)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	5,914
R-squared	0.364

Table IA.13: Financial Distress and Total Firm Sales

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of total firm sales 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. Column (1) includes industry and year fixed effects, and columns (2) and (3) include industry $\times$ year fixed effects. Column (3) includes the same firm-level control variables as in column (3) of Table 4 (coefficients not shown). All control variables are lagged one period. Variable definitions are in Table A.1 in the Appendix. Robust p -values clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.034** (0.033)	-0.031* (0.064)	-0.024 (0.180)
High Leverage	-0.033*** (0.000)	-0.034*** (0.000)	-0.032*** (0.000)
High RE	-0.008 (0.290)	-0.003 (0.734)	0.015* (0.067)
$\Delta \text{HP} < 0$	-0.005 (0.499)	-0.009 (0.273)	-0.006 (0.460)
High Leverage $\times$ High RE	0.019** (0.037)	0.018* (0.053)	0.018* (0.079)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.016 (0.104)	0.020** (0.041)	0.009 (0.420)
High RE $\times$ $\Delta \text{HP} < 0$	0.026** (0.033)	0.015 (0.256)	0.002 (0.876)
Firm-Level Controls	No	No	Yes
Industry and Year FE	Yes	No	No
Industry $\times$ Year FE	No	Yes	Yes
Observations	72,262	72,225	60,065
R-squared	0.032	0.062	0.072

Table IA.14: Sample of Firms with High Leverage and High Real Estate Assets

This table presents estimates of ordinary least squares (OLS) panel regressions at the client-supplier level. The sample consists of yearly observations of client-supplier pairs in the 2000-2015 period with suppliers having high leverage (i.e., the ratio of total debt to total assets is above the median) and high real estate assets (i.e., the ratio of PPE to total assets is above the third quartile). The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales from supplier i to client j between years $t-1$ and t . ΔHP is the change between years $t-1$ and t in the house price index (HP) of the county where the supplier is located. All control variables are lagged one period. Variable definitions are in Table A.1 in the Appendix. Robust p -values clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$\Delta HP < 0$	-0.010** (0.037)	-0.012** (0.014)	-0.014*** (0.006)
HP			0.023 (0.123)
Tobin's Q			0.039* (0.094)
Cash			-0.532** (0.021)
Assets (log)			-0.009 (0.498)
Industry and Year FE	Yes	No	No
Client $\times$ Year FE	No	Yes	Yes
Observations	1,216	1,216	885
R-squared	0.446	0.473	0.502

Table IA.15: Real Estate Assets Location

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. In addition, the sample in column 2 excludes firms with Herfindahl-Hirschman Index (HHI) of real estate holdings by state below the median. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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 column 1 is the lagged weighted average of the index in all states where firms own real estate assets. *HP* in column 2 is the lagged house price index in the county where the supplier is located. Variable definitions are in Table A.1 in the Appendix. 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) HP Weighted by Real Estate Assets by State	(2) Excluding Firms with Diversified Locations of Real Estate Assets
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.220* (0.060)	-0.482*** (0.009)
High Leverage	0.025 (0.357)	0.021 (0.477)
High RE	-0.038 (0.286)	-0.048 (0.262)
$\Delta \text{HP} < 0$	0.119** (0.015)	-0.086 (0.222)
High Leverage $\times$ High RE	0.021 (0.628)	0.020 (0.714)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.016 (0.788)	0.143 (0.216)
High RE $\times$ $\Delta \text{HP} < 0$	0.042 (0.569)	0.200 (0.103)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes
Observations	4,775	2,260
R-squared	0.381	0.425

Table IA.16: Single Segment Suppliers

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. 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. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.230** (0.029)
High Leverage	-0.022 (0.562)
High RE	-0.051 (0.364)
$\Delta \text{HP} < 0$	-0.065 (0.250)
High Leverage $\times$ High RE	0.104* (0.077)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.056 (0.359)
High RE $\times$ $\Delta \text{HP} < 0$	0.120 (0.214)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	4,780
R-squared	0.356

Table IA.17: House Price Index by MSA

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.212*** (0.003)
High Leverage	-0.004 (0.879)
High RE	-0.075** (0.041)
$\Delta \text{HP} < 0$	-0.032 (0.322)
High Leverage $\times$ High RE	0.079* (0.050)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.046 (0.265)
High RE $\times$ $\Delta \text{HP} < 0$	0.092 (0.125)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	8,188
R-squared	0.366

Table IA.18: 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 sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. In addition, the sample in each column excludes an industry with a large exposure to real estate prices based on the *RE* variable, as shown in the header. The dependent variable $\Delta \log(\text{Sales})$ 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. Regression specifications are the same as in column 2 of Table 4 (other estimated coefficients not shown). 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) Excluding Energy	(2) Excluding Utilities	(3) Excluding Telecoms	(4) Excluding Shops	(5) Excluding Manufacturing
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.108* (0.072)	-0.139** (0.026)	-0.131** (0.040)	-0.137** (0.028)	-0.111* (0.092)
Supplier Industry $\times$ Client $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,978	10,785	10,649	10,730	9,817
R-squared	0.345	0.352	0.349	0.351	0.350

Table IA.19: Real Estate Measure Excluding Leases

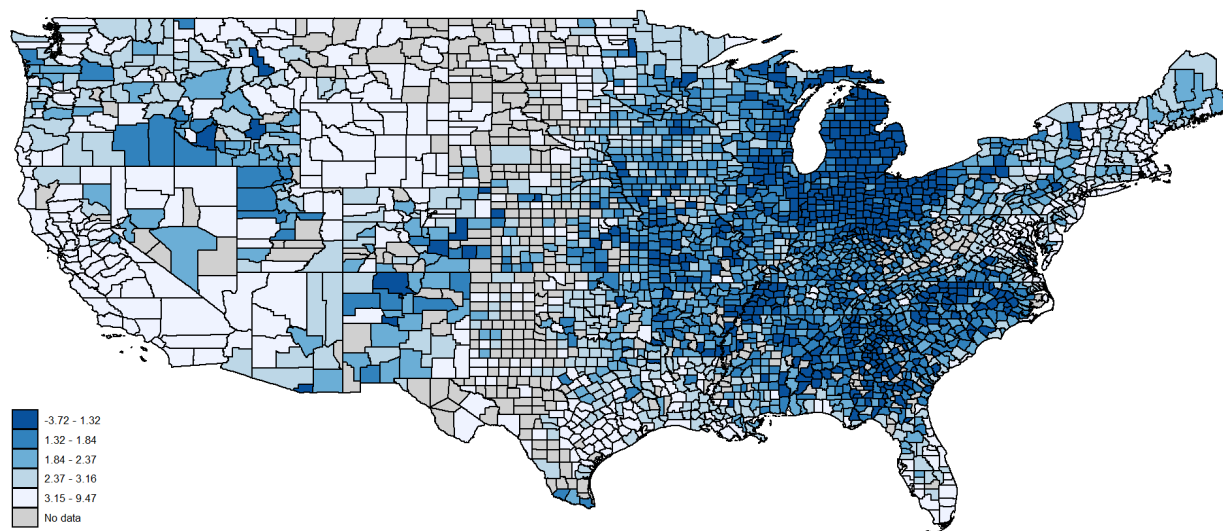
This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. The dependent variable $\Delta \log(\text{Sales})$ is the change in the log of sales 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 third quartile, and zero otherwise. $\Delta \text{HP} < 0$ 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. 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)
High Leverage $\times$ High RE $\times$ $\Delta \text{HP} < 0$	-0.151** (0.013)
High Leverage	-0.005 (0.802)
High RE	-0.063** (0.039)
$\Delta \text{HP} < 0$	-0.012 (0.706)
High Leverage $\times$ High RE	0.062* (0.075)
High Leverage $\times$ $\Delta \text{HP} < 0$	0.016 (0.622)
High RE $\times$ $\Delta \text{HP} < 0$	0.096* (0.061)
Supplier Industry $\times$ Client $\times$ Year FE	Yes
Observations	10,877
R-squared	0.353

Figure IA.1: Changes in House Price Index at the County Level

The map presents the average annual change in house price index (*HP*) at the county level during the 2000-2015 period in Panel A, and the average annual change in *HP* at the county level during the 2007-2011 period (period of poor real estate market performance) in Panel B. Counties in dark blue and light blue are in the top and bottom quintiles of the distribution of changes in *HP*. Data on *HP* is not available for counties in grey.

Panel A: Average Annual Change in House Price Index at the County Level (2000-2015)



Panel B: Average Annual Change in House Price Index at the County Level (2007-2011)

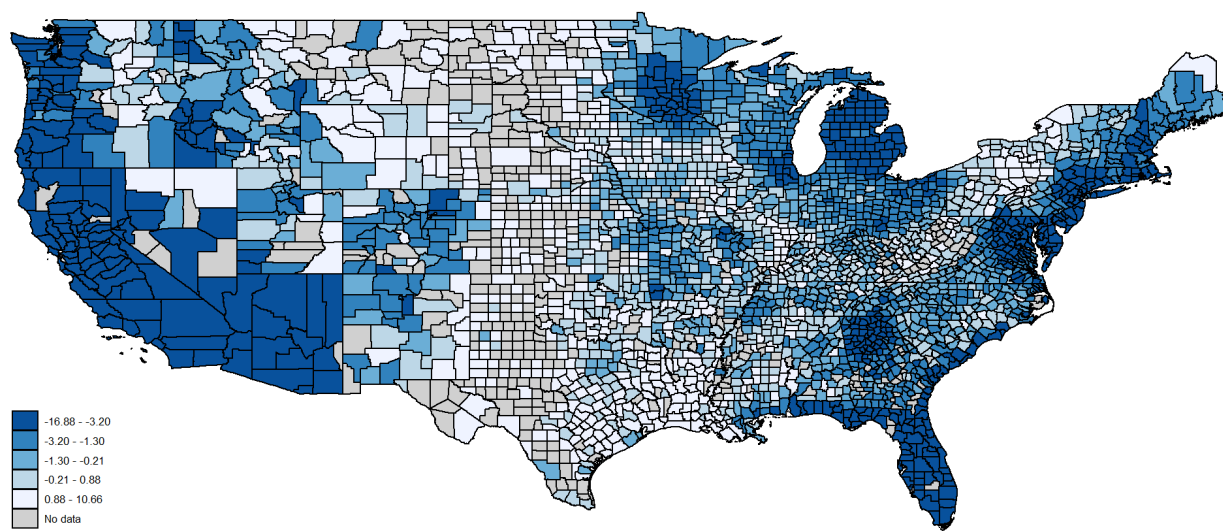
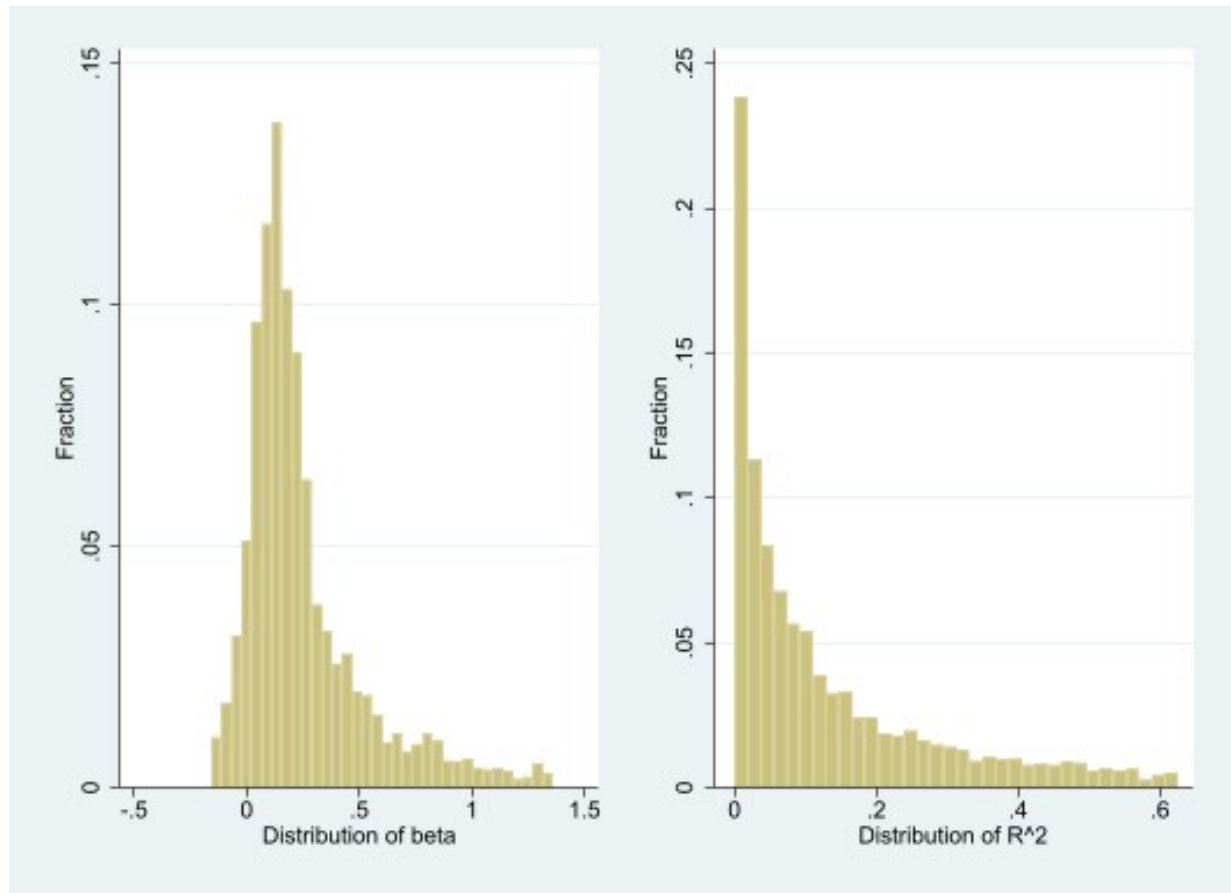


Figure IA.2: Systematic Component of County-level Real Estate Returns

This figure shows the distribution of the estimated β coefficient (left-hand panel) and the R^2 (right-hand panel) for regressions of county-level annual returns on the annual returns of S&P/Case-Shiller U.S. National Home Price Index, for all US counties from 1986 to 2016.



Appendix IA.1: Variable Definitions

Variable	Definition
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 $-1.002 \times \text{Cash Flow} + 0.283 \times \text{Tobin's } q + 3.139 \times \text{Leverage} - 39.368 \times \text{Dividends} - 1.315 \times \text{Cash}$; 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.
DD	Distance to default measure of Merton's (1974) bond pricing model estimated following the approach proposed by Bharath and Shumway (2008).
Low DD	Dummy variable that takes a value of one if DD is below 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.
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.
Adjusted RE	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 Adjusted RE	Dummy variable that takes a value of one if Adjusted RE is above the third quartile, and zero otherwise.

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