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Indirect Costs of Financial Distress*

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Abstract

We estimate the indirect costs of financial distress due to lost sales by exploiting real estate (RE) shocks and cross-supplier variation in RE 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 RE 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.

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

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

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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.

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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 article, 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 markups (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 USA sourced from the Compustat Segment database for the 2000–15 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 (RE) prices as shocks to the collateral value of firms. We use the value of RE assets and leverage to determine the exposure to drops in RE prices (the treatment). The value of RE assets is proxied by the ratio of property, plant, and equipment (PPE) to total assets, knowing that RE assets account for more than 80% of PPE (Cvijanović, 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 RE shocks on firms with high RE assets and high leverage relative to otherwise similar firms.

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 KZ index of financial constraints (Kaplan and Zingales, 1997), and Merton's (1974) measure of distance to default.

Local RE 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 RE market, especially when suppliers and clients are located in different counties. Moreover, shocks to RE 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 RE assets can be used as collateral, firms with more leverage tend to be those that own more RE as a fraction of their total assets and are therefore more exposed to adverse shocks. RE shocks have been shown to impact investment and financial policies through this collateral channel (e.g. Gan, 2007; Chaney, Sraer, and Thesmar, 2012; Cvijanović, 2014); therefore, we expect clients to respond to these shocks if they suspect the supplier is in financial 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 RE prices, they might still become aware that a supplier is in financial distress; for example, they could experience a decrease in quality or delays in dispatching orders (Cohn and Wardlaw, 2016; Kini *et al.*, 2017).[4] Consistent with this idea, we show that shocks to RE 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 Cvijanović (2014) and provide support to the notion that negative RE 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 RE 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 that lend 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 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, that is suppliers that are more affected by a decline in local RE prices when compared to otherwise similar suppliers that are less affected. Our estimates are economically significant: a

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 in financial distress suffers a 13% stronger reduction in sales when there is a drop in local RE 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 RE 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 RE prices, relative to other suppliers of the same client. Using the land supply elasticity instrument for RE prices of Saiz (2010), we estimate our results in a subsample of counties with high land supply elasticity, where RE 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 requires 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 the within-firm variation in (distressed) multi-segment firms with high RE 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 RE 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, 1998). We conclude that the indirect costs of financial distress are sufficiently sizable to be an important consideration in capital structure decisions.

Our article 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 article is related to the literature on the impact of RE 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.* (2022) show that firms take on new debt following an increase in the value of their RE, but through unsecured debt, rather than mortgages or any other form of secured debt. We contribute to this literature by estimating the indirect costs of financial distress due to RE shocks through the balance sheet channel.[7]

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.

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 the 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.

Our article 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 RE 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 USA. 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 USA must disclose, on a yearly basis, the identity of clients and the sales to clients whose purchases represent more than 10% of the total sales. We collect this information from the Compustat Segment database for 2000–15. 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. Appendix Table A.1 provides the variable definitions.

In our estimations, we use RE prices as shocks to the collateral value of firms with RE 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 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, 1989; 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 RE assets to measure its exposure to RE shocks. Since information about corporate RE assets is only available in Compustat until 1993, in our main estimations, we use the book value of PPE as a proxy for them. Corporate RE assets account for more than 80% of PPE (Cvijanović, 2014). Moreover, the ratio of PPE to total assets is highly correlated with the ratio of the book value of corporate RE assets to total assets, with a correlation coefficient of 0.82.

We obtain the headquarters location of suppliers at the county level from Compustat, and house prices (HPs) 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 HPs at the MSA level.

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.

Since a firm's RE assets are not always located in the same county as their headquarters, our proxy of the exposure to RE 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.* (2022) compute the market value of corporate RE assets using commercial RE transaction data, including the geographical location of a firm's RE assets. They find that the average firm has only \$100 million (6% of the RE assets) in market value at locations outside of the region of their headquarters, and that the market value of RE assets based on the headquarters and the actual locations of these assets displays a high degree of correlation.

At the cost of a significant reduction in the sample size, and sample selection toward older firms that were active in 1993, in robustness tests, we proxy for a supplier's exposure to the local RE market each year using alternative measures. We use the market value of RE 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 RE assets in 1993 is obtained by inflating the historical cost of a firm's RE assets from the year of acquisition using the HP Index. The average age of a firm's RE 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 2000–15, 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 I contain the descriptive statistics. Panel A presents summary statistics for the suppliers. The average book (market) leverage corresponds to 24.2% (20.8%) of the 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 RE assets, which corresponds to the ratio of PPE to the total assets, is 23.3%, although this is highly variable across firms. This measure is highly correlated with the ratio of RE assets to total assets over 1976–93, the period in which data on RE assets are available. However, this variable is likely overestimating the true ratio of RE assets to total assets, leading to measurement error that could lead to an attenuation bias in our estimations. Indeed, RE assets account on average (median) for 66.4% (81.1%) of PPE in 1976–93.

Panel B of Table I 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 RE 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 HPs.

Supplementary Appendix Table IA.1 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 RE shocks of slightly more than five suppliers per client each year on average. There is also a large time series variation in RE asset prices. On average, the RE 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.

Table I. Summary statistics

The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 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.
Δlog (Sales)	0.030	0.038	0.512	−0.809	0.834	10,331	15,214
Leverage	0.242	0.175	0.288	0.000	0.697	10,331	15,214
High Leverage	0.436	0.000	0.496	0.000	1.000	10,331	15,214
Market Leverage	0.208	0.121	0.242	0.000	0.742	9,411	13,987
Short-term Leverage	0.045	0.006	0.121	0.000	0.211	10,331	15,214
KZ Index	−10.055	−1.571	32.129	−49.290	3.639	8,740	12,981
High KZ Index	0.398	0.000	0.490	0.000	1.000	8,740	12,981
HP	6.021	5.006	3.209	2.415	12.758	10,331	15,214
ΔHP	0.040	0.035	0.079	−0.083	0.175	10,331	15,214
ΔHP < 0	0.291	0.000	0.454	0.000	1.000	10,331	15,214
RE	0.233	0.158	0.223	0.018	0.766	10,331	15,214
High RE	0.249	0.000	0.432	0.000	1.000	10,331	15,214
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.
Δlog (Sales)	0.030	0.038	0.512	−0.809	0.834	2,844	15,214
Leverage	0.258	0.247	0.166	0.042	0.601	2,023	11,983
High Leverage	0.551	1.000	0.497	0.000	1.000	2,023	11,983
Market Leverage	0.260	0.185	0.228	0.017	0.838	1,872	11,558
HP	5.592	4.489	3.179	2.607	12.836	2,031	11,995
ΔHP	0.035	0.034	0.073	−0.074	0.155	2,031	11,995
ΔHP < 0	0.295	0.000	0.456	0.000	1.000	2,031	11,995
RE	0.307	0.256	0.223	0.032	0.637	2,027	11,995
High RE	0.430	0.000	0.495	0.000	1.000	2,027	11,995
Tobin's q	1.767	1.497	1.052	0.928	3.682	1,562	9,398
Cash	0.074	0.055	0.065	0.006	0.196	2,008	11,724
Assets (log)	10.614	10.620	1.418	8.335	12.620	2,027	11,995

Thus, the fraction of suppliers located in counties with negative price changes varies from virtually 0% in 2000–05 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 HPs. Supplementary Appendix Figure IA.1 shows that there is also a large geographical variation in the change in RE prices across counties. Supplementary Appendix 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 RE on the returns of S&P/Case-Shiller U.S. National Home Price Index for the sample of all US counties from 1986 to 2016 at the yearly frequency. County-level RE returns are mostly explained by idiosyncratic factors as opposed to systematic factors, which is consistent with the notion that RE 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 an RE 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:

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

where i denotes suppliers and j denotes clients. The dependent variable ($\Delta\ln(\text{Sales})_{\text{ijt}}$) measures the percentage change in the supplier's sales to each client, which is our measure of economic distress.[10] $(\Delta\text{HP} < 0)_{\text{it}}$ is a dummy variable that takes a value of one if the HP Index in the county, where supplier i is located, drops between year $t-1$ and year t, and is zero otherwise. High $\text{RE}_{i,t-1}$ is a dummy variable that takes a value of one if the supplier i ratio of PPE to total assets is above the 75th percentile of the distribution. High $\text{Leverage}_{i,t-1}$ 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 RE price, RE 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 RE assets and high leverage relative to otherwise similar firms following an RE shock is significant. A negative coefficient would indicate that clients reduce their purchases from suppliers more affected by RE shocks (i.e. highly levered firms with large RE assets) and would support the notion that clients typically reduce their exposure to suppliers in financial distress.[11]

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 nonmissing 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.

Our client–supplier data allow us to include client-by-year fixed effects in Equation (1), which ensure 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 HPs 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 $(\Delta\text{HP} < 0)_{\text{it}}$, $\text{RE}_{i,t-1}$, and High $\text{Leverage}_{\text{i},t-1}$, 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 HP Index. 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.a. *Balance tests*

We conduct balance tests to compare the observable characteristics of high leverage and high RE assets firms located in counties that suffered an RE shock $\Delta\text{HP} < 0$, with high leverage and high RE assets firms located in counties that did not suffer an RE shock $\Delta\text{HP} \geq 0$. Our main estimates assume that these two groups are otherwise similar absent the RE shock. We report t-tests of the differences as well as normalized differences in Table II. 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 RE prices ($\Delta\text{HP} < 0$) and other firms ($\Delta\text{HP} \geq 0$) are virtually identical in terms of average leverage and RE 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.b. *Relevance condition*

Another identifying assumption we make is that drops in the value of RE assets lead to financial distress in firms with high leverage and high RE assets. Table III 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 (Δ*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

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.

Table II. Sample balance tests

In this table, we compare the characteristics of high leverage and high RE assets firms located in counties that suffered an RE shock ΔHP<0 (treatment group) with high leverage and high RE assets firms located in counties that did not suffer an RE shock ΔHP≥0 (control group). The normalized difference is $\Delta_x = \frac{\overline{X}_t - \overline{X}_c}{\sqrt{S_t^2 + S_c^2}}$, where $\overline{X}_t$, $\overline{X}_c$ 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 2000–15 period. The sample in Panel B consists of yearly observations of Compustat firms in the 2000–15 period. Variable definitions are in Table A.1 in the Appendix.

Panel A: Supplier–Client Sample

	ΔHP ≥ 0 (Observations = 1,488)		ΔHP < 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

	ΔHP ≥ 0 (Observations = 9,510)		ΔHP < 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

the dependent variable (Column 3). This is a dummy variable that takes a value of one if the auditor expressed doubts about 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]

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

Table III. 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 ΔDistance 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 about 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. $\Delta HP < 0$ is a dummy variable that takes a value of one if the change between years $t-1$ and t in the HP Index 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 2000–15 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.

	ΔDistance to default (1)	Covenant violation (2)	Doubts of going concern (3)
High Leverage × High RE × ΔHP < 0	−0.644***	0.031*	0.020*
	(0.001)	(0.060)	(0.091)
High Leverage	0.268***	0.049***	0.101***
	(0.000)	(0.000)	(0.000)
High RE	−0.096	0.010	0.005
	(0.212)	(0.151)	(0.449)
ΔHP < 0	−0.206**	0.017***	0.017***
	(0.045)	(0.000)	(0.001)
High Leverage × High RE	0.011	−0.003	−0.066***
	(0.906)	(0.724)	(0.000)
High Leverage × ΔHP < 0	0.392***	−0.044***	−0.018**
	(0.000)	(0.000)	(0.022)
High RE × ΔHP < 0	0.498***	−0.002	0.001
	(0.002)	(0.825)	(0.859)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	48,960	44,950	59,113
R^2	0.086	0.039	0.065

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 RE 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 RE asset firms are more likely to experience covenant violations and going concern audit opinions. An auditor that raises doubts about the viability of a firm as a going concern considers "soft" information obtained 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 (vs. low) leverage and high (vs. low) RE assets are more likely (vs. unlikely) to face financial distress when there is a drop in local RE prices.[14]

2.4.c. ***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 USA. 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 IV presents the results of estimating our main regression at the supplier–client level in Equation (1) using different variables to measure the change in RE 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 HP Index 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 RE prices. In the regression for 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 is zero otherwise. The dependent variable in all specifications is the percentage change in the supplier's sales to each client ($\Delta\ln(\text{Sales})_{ijt}$).

The results in Column (1) show that the coefficient of the triple interaction (High Leverage $\times$ High RE $\times$ ΔHP < 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 HPs, sales decline 10.4% more for high RE 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 substitute the client-by-year fixed effects with supplier industry-by-client-by-year fixed effects. In

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 forty bankruptcies and less than twenty 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.

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 = 0.000).

Table IV. Baseline results

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier i to client j between years $t-1$ and t. 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 HP Index 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 RE 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) ΔHP < 0	(2) ΔHP < 0	(3) ΔHP < 0	(4) ΔHP< −3.3%	(5) ΔHP	(6) $\Delta HP_{t-2 \to t-1}<0$
High Leverage × High RE × ΔHP	−0.104**	−0.133**	−0.119*	−0.136*	0.010**	−0.114*
	(0.025)	(0.032)	(0.072)	(0.096)	(0.038)	(0.067)
High Leverage	0.004	−0.001	−0.006	−0.004	0.009	0.005
	(0.789)	(0.956)	(0.765)	(0.808)	(0.599)	(0.785)
High RE	−0.024	−0.055*	−0.041	−0.044*	−0.009	−0.051*
	(0.249)	(0.062)	(0.176)	(0.097)	(0.724)	(0.089)
ΔHP	−0.009	−0.011	−0.019	−0.037	0.001	−0.012
	(0.709)	(0.736)	(0.588)	(0.242)	(0.739)	(0.709)
High Leverage × High RE	0.030	0.050	0.050	0.033	−0.019	0.041
	(0.244)	(0.145)	(0.174)	(0.284)	(0.536)	(0.231)
High Leverage × ΔHP	0.014	0.010	0.001	0.037	−0.002	−0.009
	(0.558)	(0.763)	(0.974)	(0.376)	(0.382)	(0.781)
High RE × ΔHP	0.067*	0.093*	0.100*	0.096	−0.006*	0.088*
	(0.066)	(0.075)	(0.069)	(0.112)	(0.099)	(0.095)
Supplier Controls	No	No	Yes	No	No	No
Client × Year FE	Yes	No	No	No	No	No
Supp. Industry × Client × Year FE	No	Yes	Yes	Yes	Yes	Yes
Observations	15,214	10,877	9,012	10,877	10,877	10,896
R^2	0.286	0.353	0.366	0.353	0.353	0.352

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

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

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 RE 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 HPs, ΔHP less than –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 HPs, ΔHP, rather than a dummy variable. In Column (5), the estimated triple interaction coefficient is statistically significant at conventional levels. We then measure HP shocks as a dummy variable taking a value of one if HPs fell between years $t-2$ and $t-1$, that is 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 ($p = 0.067$).

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 RE holdings in a county without a drop in RE prices. More generally, we analyze 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 RE Assets

In Table V, we consider alternative measures for the suppliers' RE assets. In Column (1), our measure of RE assets follows Chaney, Sraer, and Thesmar (2012) and is based on the market value of RE 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 IV, but the estimated coefficient is of the same order of magnitude to what is in Table IV, 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 HPs, relative to another supplier in the same industry with a lower exposure to these shocks.

In Column (2), we examine RE exposure using commercial RE data (Campello *et al.*, 2022), 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 RE assets.[18] In Column (3), we estimate the RE 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 RE assets to PPE during the 1976–93 period (adjusted RE); the book value of RE 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 toward older firms

17 Supplementary Appendix Table IA.3 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 levels (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 levels.

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.* (2022), we winsorize this variable at the 5% level.

Table V. Alternative measures of RE assets

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years $t-1$ and *t*. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. ΔHP <0 is a dummy variable that takes a value of one if the change between years $t-1$ and *t* in the HP Index 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 RE in 1993 by the change in the market value of RE 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 RE based on the transaction data and the true geographical location of the firms' RE 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, and zero otherwise. Industry RE is the product of the ratio of PPE to the total assets by the average industry-level ratio of RE 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 × High RE × ΔHP < 0	−0.148*	−0.124*	−0.279***	−0.167*
	(0.081)	(0.073)	(0.006)	(0.060)
High Leverage	−0.099**	−0.004	0.002	0.000
	(0.019)	(0.940)	(0.914)	(0.998)
High RE	−0.141***	−0.040	−0.037	−0.094**
	(0.008)	(0.400)	(0.415)	(0.021)
ΔHP < 0	−0.034	0.046	0.018	−0.010
	(0.397)	(0.344)	(0.625)	(0.737)
High Leverage x High RE	0.140**	0.028	0.100*	0.081**
	(0.033)	(0.673)	(0.056)	(0.048)
High Leverage × ΔHP < 0	0.036	0.027	−0.011	0.000
	(0.417)	(0.625)	(0.758)	(0.990)
High RE × ΔHP < 0	0.139*	0.148***	0.146*	0.160*
	(0.060)	(0.006)	(0.074)	(0.056)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes
Observations	943	950	4,496	10,877
R^2	0.417	0.451	0.408	0.353

that are likely to be less financially constrained (Hadlock and Pierce, 2010). In the regression for Column (4), we use an industry-adjusted measure of RE assets (Industry RE). This measure imputes the missing value of RE assets (post-1993) as the product of the PPE to total assets ratio in year *t* by the industry average RE assets to PPE ratio during 1976–93.

Overall, our results in Table V are robust to using alternative measures of RE assets. The coefficients are of similar magnitude to those in Table IV, 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 RE prices may be endogenous to the demand for a firm's products or services. A local economic shock could affect both RE 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 RE shocks due to different levels of RE assets and leverage. Thus, changes in a client's purchases due to a differential impact of local RE shocks and/or economic shocks are 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 RE shocks.

To further validate our identification strategy, we estimate placebo regressions using the specification used to generate the results in Column (2) of Table IV. We estimate the coefficient of the triple interaction, High Leverage $\times$ High RE $\times$ ΔHP < 0, in regressions in which we fix the RE 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 RE assets and leverage in the absence of the RE shock. To study the parallel trends assumption, we evaluate whether the trends in sales for products or services for high RE assets and high leverage relative to otherwise similar firms are the same before the RE 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 IV, and the coefficient at year +1 is also negative and significant. The effect does not persist beyond 2 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 RE prices relative to other suppliers of the same client. This should be more of a concern in regions where RE prices are likely to be more responsive to economic prospects. Following Saiz (2010), who uses land supply elasticity as an instrument for RE prices, we estimate Equation (1) using a subsample of counties with high land supply elasticity where RE 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 VI shows our estimates for a subsample of suppliers located in counties with high land supply elasticity (elasticity above one). Our

19 The coefficients in Table V correspond to the specification in Column (2) of Table IV.

20 This instrument is difficult to apply directly to drops in real estate prices, which is our variable of interest $(\Delta\text{HP} < 0)_{it}$. 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.

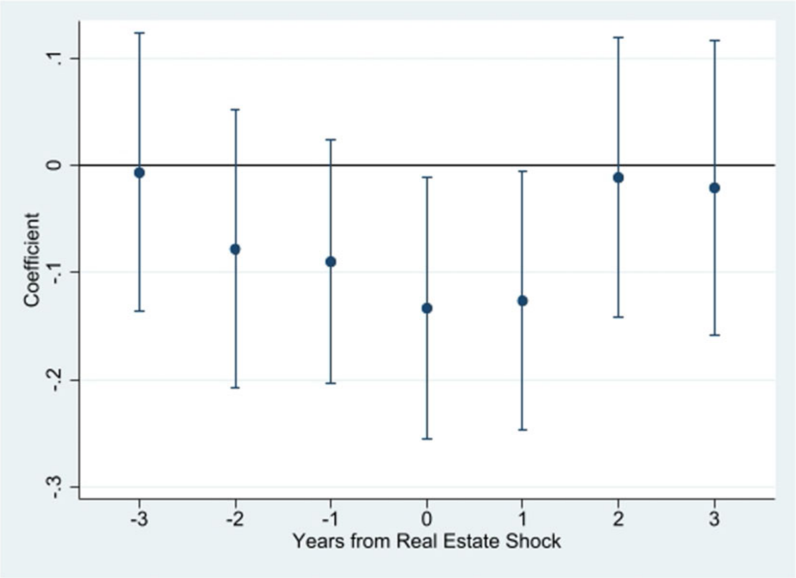

Figure 1. Placebo regressions.
This figure shows the coefficient and 90% confidence intervals of the triple interaction, High Leverage $\times$ High RE $\times$ ΔHP <0, in OLS panel regressions at the supplier–client pair level. The dependent variable is Δlog(Sales), defined as the change in the log of sales from supplier i to client j between years $t+k-1$ and $t+k$ ($k=-3, -2, \ldots, +3$). 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 PPE to assets in $t-1$ is above the third quartile, and zero otherwise. ΔHP <0 is a dummy variable that takes a value of one if the change between years t and $t-1$ in the HP 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 IV. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period.

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 VI, 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. the financial distress of a supplier is the direct cause of the local RE 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 the 5% level.

Another issue is that there may be omitted factors that are correlated with both the firm's decision to own RE and the demand for its products. A firm may be simultaneously more likely to own RE assets and be more sensitive to local economic conditions. To address this issue, we control for the interaction of initial firm characteristics and RE prices

21 We update the Saiz (2010) housing supply elasticity data for housing elasticities to cover our 2000–15 sample period. We thank Manuel Adelino for providing us with the updated data.

Table VI. Local economic conditions

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 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 Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years $t-1$ and *t*. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. High RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 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 HP 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. *, **, and *** indicate statistical significance at the 10, 5, and 1% level, respectively.

	(1) High supply elasticity	(2) Small suppliers in large counties
High Leverage × High RE × $\Delta HP < 0$	−0.118*	−0.189**
	(0.054)	(0.013)
High Leverage	0.009	−0.001
	(0.816)	(0.962)
High RE	−0.010	−0.068**
	(0.659)	(0.042)
$\Delta HP < 0$	−0.043	−0.031
	(0.147)	(0.395)
High Leverage × High RE	0.054	0.064
	(0.122)	(0.113)
High Leverage × $\Delta HP < 0$	0.074	0.004
	(0.178)	(0.916)
High RE × $\Delta HP < 0$	0.030	0.108*
	(0.474)	(0.081)
Supplier Industry × Client × Year FE	Yes	Yes
Observations	5,686	8,782
R^2	0.423	0.359

using the HP level. Column (1) in Supplementary Appendix Table IA.4 shows that the triple interaction coefficients are similar to those in Table IV.

A more general concern is that negative RE shocks could affect different firms in our sample differently. For instance, negative RE shocks might affect small and large firms differently, and because size is correlated with financial constraints, this heterogeneous response of firms of different sizes could be 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 Supplementary Appendix Table IA.4. Our main results remain unchanged. We conclude that the differential response to RE prices across suppliers with different characteristics can be attributed to the RE collateral channel.

A key identifying assumption is that declining RE prices in the supplier's headquarter 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), RE prices, and other city-level variables (Dougal, Parsons, and Titman, 2015, 2022). Therefore, one concern is that decreases in RE 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 Supplementary Appendix Table IA.5, 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 RE 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 Supplementary Appendix Table IA.6 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 IV at about −17%.

In Panel B of Supplementary Appendix Table IA.6, we present regression results for the subsamples of client–supplier pairs in which the geographical 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). In contrast, the triple interaction coefficient is negative and statistically significant in the sample of client–suppliers located further away from each other (high distance sample). We conclude that clients are more likely to reduce purchases from suppliers in financial distress when the suppliers are geographically distant. This may be explained by information asymmetry between clients and suppliers, as clients may be less informed about suppliers that are further away. Less informed clients might not be able to distinguish between temporary financial distress triggered by an RE 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

22 A related concern is that the double interaction term High RE $\times$ ΔHP is positive and statistically significant in some specifications of Table IV, 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 $\times$ ΔHP, High RE, and ΔHP) is positive but statistically insignificant.

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

3.6.a. *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 a 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 VII 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 – Lerner Index (where the Lerner Index is the median net margin in each industry and year), and 1 – net margin (at the firm level). Columns (3)–(8) in Table VII 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, that is high number of firms, high 1 – Lerner Index, and high 1 – 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.b. *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 will 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 on durable goods.

Table VII. Supplier market share and product market competition

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years *t* − 1 and *t*. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. High RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the third quartile, and zero otherwise. ΔHP <0 is a dummy variable that takes a value of one if the change between years *t* − 1 and *t* in the HP Index 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 (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)	Low (7)	High (8)
High Leverage ×	−0.218*	−0.084	−0.113*	−0.248**	−0.076	−0.157*	−0.071	−0.213**
High RE × ΔHP < 0	(0.090)	(0.201)	(0.060)	(0.032)	(0.404)	(0.078)	(0.432)	(0.031)
High Leverage	0.006	0.002	−0.017	0.004	−0.002	−0.001	0.018	0.011
	(0.880)	(0.918)	(0.419)	(0.895)	(0.950)	(0.963)	(0.454)	(0.747)
High RE	−0.122**	−0.021	−0.042	−0.086*	−0.047	−0.052	−0.032	−0.120**
	(0.019)	(0.514)	(0.141)	(0.078)	(0.418)	(0.150)	(0.460)	(0.012)
ΔHP < 0	−0.028	0.009	−0.008	−0.002	−0.021	−0.002	0.023	−0.057
	(0.638)	(0.771)	(0.771)	(0.972)	(0.642)	(0.959)	(0.524)	(0.367)
High Leverage ×	0.116*	0.019	0.021	0.134**	0.058	0.047	0.037	0.104*
High RE	(0.100)	(0.579)	(0.537)	(0.024)	(0.328)	(0.284)	(0.496)	(0.057)
High Leverage ×	−0.024	0.005	0.016	0.003	0.012	0.001	−0.051	0.097
ΔHP < 0	(0.750)	(0.856)	(0.617)	(0.955)	(0.791)	(0.985)	(0.167)	(0.160)
High RE × ΔHP < 0	0.168*	0.056	0.092*	0.131	0.090	0.098	0.100	0.135*
	(0.090)	(0.306)	(0.064)	(0.163)	(0.363)	(0.148)	(0.245)	(0.078)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,891	4,621	4,474	5,830	2,206	8,164	3,935	4,990
R^2	0.362	0.420	0.416	0.341	0.392	0.346	0.408	0.365

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 VIII 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,

Table VIII. Durable goods and manufacturing

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years $t-1$ and t. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. High RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 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 HP Index 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 (1)	Non-durable goods (2)	Non-manufacturing industries (3)	Manufacturing industries (4)
High Leverage × High RE × $\Delta HP < 0$	−0.149**	0.006	−0.111*	−0.497***
	(0.036)	(0.933)	(0.092)	(0.000)
High Leverage	0.004	−0.031	0.002	−0.024
	(0.865)	(0.267)	(0.934)	(0.546)
High RE	−0.053	−0.048	−0.065**	−0.008
	(0.107)	(0.320)	(0.046)	(0.855)
$\Delta HP < 0$	−0.009	−0.018	−0.006	−0.127*
	(0.814)	(0.641)	(0.866)	(0.054)
High Leverage × High RE	0.054	0.002	0.049	0.070
	(0.162)	(0.967)	(0.189)	(0.231)
High Leverage × $\Delta HP < 0$	0.008	0.012	−0.001	0.176**
	(0.846)	(0.808)	(0.974)	(0.040)
High RE × $\Delta HP < 0$	0.093	0.043	0.087	0.325**
	(0.121)	(0.489)	(0.117)	(0.011)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes
Observations	9,569	1,285	9,817	947
R^2	0.357	0.268	0.350	0.420

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.c. *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

Table IX. Specificity in supplier product market

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years $t-1$ and *t*. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. High RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the 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 HP Index 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 × High RE × ΔHP < 0	−0.255**	−0.044	−0.175*	−0.040	−0.388*	−0.009
	(0.011)	(0.604)	(0.074)	(0.844)	(0.100)	(0.892)
High Leverage	−0.052**	0.023	0.000	0.077*	−0.012	0.012
	(0.039)	(0.369)	(0.997)	(0.087)	(0.902)	(0.538)
High RE	−0.084*	−0.028	−0.080**	0.099	−0.032	−0.021
	(0.055)	(0.527)	(0.044)	(0.219)	(0.748)	(0.492)
ΔHP < 0	−0.047	−0.003	−0.061	0.038	−0.109	0.012
	(0.363)	(0.944)	(0.281)	(0.580)	(0.343)	(0.711)
High Leverage × High RE	0.126***	0.002	0.048	−0.091	0.111	−0.016
	(0.006)	(0.979)	(0.300)	(0.348)	(0.348)	(0.659)
High Leverage × ΔHP < 0	0.095	−0.027	0.068	−0.058	0.153	−0.026
	(0.103)	(0.510)	(0.246)	(0.482)	(0.443)	(0.388)
High RE × ΔHP < 0	0.217**	0.008	0.147*	0.018	0.332**	0.008
	(0.018)	(0.902)	(0.053)	(0.895)	(0.033)	(0.883)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,989	6,889	4,379	2,132	1,627	7,423
R^2	0.440	0.341	0.389	0.419	0.433	0.386

capture restrictions on alternative sources of inputs. Table IX 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]

3.6.d. *Client–supplier relationship*

If there is a strong relationship and dependence between the 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). Supplementary Appendix Table IA.7 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 Section 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 geographical 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 IV suggest that shocks to RE 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.

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.

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 RE holdings with probability p_t, and there can be a negative shock to RE prices with probability q_t. Each period, firms that suffer a shock to RE 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 $M = 0.196$ (0.133×1.47). For simplicity, we assume that (i) for every t, $p_t = p$ and $q_t = q$ and are i.i.d. random variables; (ii) p is independent of q; and (iii) 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 RE 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 X 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 RE assets firms (0.25); and $p = 0.100$, the fraction of counties that suffer a drop in RE 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 the 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 an RE crisis, and for firms with a 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 the 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 RE 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).

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.

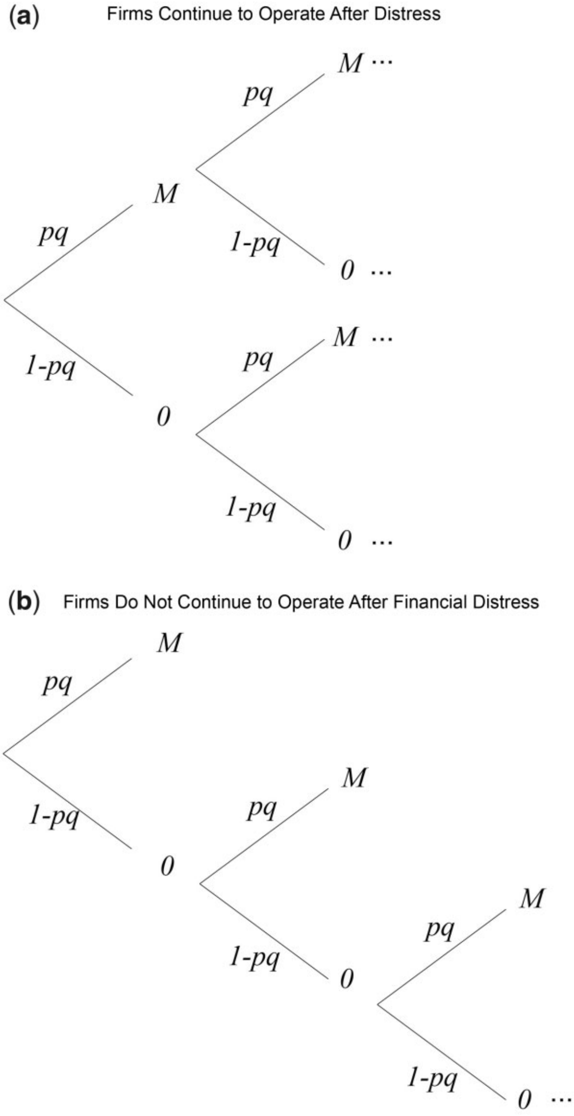

Figure 2. Model for the indirect costs of financial distress
This figure illustrates a simple model of the indirect costs of financial distress implied by our estimates. **Each period, a firm can be highly levered and have high RE holdings with probability p, and there can be a shock to RE prices with probability q, with p and q i.i.d random variables that are independent of each other. Firms that suffer a shock to RE 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).

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

Table X. 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 RE holdings. q is the probability of an** RE 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

what initiates the 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' investments in working capital and fixed assets below.

3.8.a. *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. In 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 RE assets and high leverage that suffer a negative RE shock in the 2000–15 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 XI, we show that the reduction in sales is more pronounced for durable goods

Table XI. Sales of multi-segment distressed firms

This table presents estimates of OLS panel regressions at the supplier-segment level. The sample consists of yearly observations of Compustat Segments in the 2000–15 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 HP Index of the county where the firm is located is negative. The dependent variable Δlog(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***	−0.182***	−0.213**
	(0.000)	(0.000)	(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 × Year FE	No	No	Yes
Observations	7,239	5,633	5,337
R^2	0.020	0.023	0.042

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.b. *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 XII, 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 the

Table XII. Investment in working capital and fixed assets

This table presents estimates of OLS panel regressions at the supplier–client pair level. The sample consists of yearly observations of Compustat supplier–client pairs in the 2000–15 period. The dependent variable Δlog(Sales) is the change in the log of sales from supplier *i* to client *j* between years *t*–1 and *t*. High Leverage is a dummy variable that takes a value of one if the ratio of total debt to total assets is above the median, and zero otherwise. High RE is a dummy variable that takes a value of one if the ratio of PPE to total assets is above the third quartile, and zero otherwise. ΔHP <0 is a dummy variable that takes a value of one if the change between years *t* – 1 and *t* in the HP Index 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 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 (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
High Leverage × High RE × ΔHP < 0	−0.124**	−0.140	−0.138	−0.129*	−0.103*	−0.171*
	(0.021)	(0.280)	(0.228)	(0.063)	(0.085)	(0.079)
High Leverage	−0.011	0.007	−0.038	0.003	−0.018	0.008
	(0.563)	(0.875)	(0.381)	(0.894)	(0.457)	(0.773)
High RE	−0.056*	−0.092	−0.047	−0.057	−0.038	−0.070
	(0.091)	(0.134)	(0.386)	(0.135)	(0.213)	(0.104)
ΔHP < 0	−0.029	0.013	0.016	−0.017	−0.023	−0.013
	(0.308)	(0.846)	(0.799)	(0.643)	(0.491)	(0.753)
High Leverage × High RE	0.046	0.077	0.085	0.052	0.018	0.077
	(0.225)	(0.249)	(0.162)	(0.268)	(0.632)	(0.127)
High Leverage × ΔHP < 0	0.009	−0.003	0.032	0.008	0.019	0.010
	(0.763)	(0.964)	(0.664)	(0.837)	(0.637)	(0.819)
High RE × ΔHP < 0	0.078	0.143	0.108	0.058	0.086*	0.106
	(0.103)	(0.166)	(0.265)	(0.299)	(0.072)	(0.187)
Supplier Industry × Client × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,313	4,189	3,071	7,568	2,937	7,495
R^2	0.409	0.312	0.404	0.335	0.394	0.349

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]

4. Extensions and Robustness

4.1 Alternative Measures of Financial Constraints

Our main measure of financial constraints is book leverage. In Supplementary Appendix Table IA.9, 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 IV.

In the regression for Column (4) of Supplementary Appendix 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 1 year) as opposed to long-term debt. The point estimate of the triple interaction coefficient is slightly larger than the one in Column (4). Last, Column (6) of Supplementary Appendix 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). The estimate of the coefficient of the triple interaction is 0.034 and is statistically significant. The results in Supplementary Appendix Table IA.9 show that overall our findings are consistent across different measures of financial constraints.

25 In a related analysis, Supplementary Appendix Table IA.8 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 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.

4.2 Extensive Margin

Our baseline results in Table IV are determined under the assumption that clients and suppliers maintain their relationship during the year of the RE 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. Supplementary Appendix Table IA.10 presents the results. The coefficients are between 0.054 and 0.097 and are statistically significant in four out of six regressions. This suggests that clients stop buying large amounts from a supplier when the supplier experiences an RE shock. The coefficients indicate that the probability of losing a client after an RE 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 RE shocks, which can result in the decline or loss of some client–supplier relationships.[26]

4.3 Robustness and Extensions

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

The mechanism that we explore is more likely when there are large negative changes in RE prices such as those that took place during the 2007–09 financial crisis and the 2007–11 RE crisis. We estimate our baseline specifications for these periods and present the results in Supplementary Appendix 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 2000–15 sample period, the sum of reported sales represents, on average, 37% of the 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). Supplementary Appendix 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 IV using the change in total sales as a dependent variable. Supplementary Appendix 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 RE assets are endogenous, which may compromise our identification strategy. We restrict our sample to firms with high leverage and high RE assets; thus, we are just exploiting the variation in RE prices.

26 A caveat is that when we do not observe such transactions, it may not necessarily indicate that a client stops buying from a supplier, but instead that this client's purchases are not above the 10% threshold imposed for reporting purposes.

Supplementary Appendix Table IA.14 shows a significant reduction in sales following a drop in HPs. Although this approach is more limited in terms of the external validity of the results, it improves 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 RE 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' RE 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 the RE assets located in each state (Garcia and Norli, 2012). The sample in this case is smaller. Column (1) in Supplementary Appendix Table IA.15 reports the results. The results are consistent with our baseline results in Table IV 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 RE assets across states is below the median. Thus, we focus on firms whose RE is more concentrated in each state. The results are also consistent with our baseline estimates. In Supplementary Appendix Table IA.16, we restrict the sample to suppliers that operate in a single business segment. For these nondiversified suppliers, RE 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 HPs. As an alternative, we use MSA-level prices. Supplementary Appendix Table IA.17 reports the results. We find that the magnitude of the triple interaction coefficient is larger than in Table IV, and equals –21%.

Supplementary Appendix Table IA.18 reports the results when we exclude the sample industries with high exposure to RE 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 IV with point estimates between –14% and –10.8%.

Our baseline results include RE 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 a robustness check, we exclude leases from our definition of RE assets. Supplementary Appendix 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 RE shocks for the 2000–15 period. We identify the effects of financial distress by exploiting cross-supplier variation in RE assets and leverage, as well as the timing of RE shocks. We find that clients reduce their reliance on suppliers that are in financial distress triggered by a county-level RE 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 RE prices. Thus, changes in a client's purchases due to a differential impact of local RE shocks and/or economic shocks are 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 RE 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 the 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.

Data Availability

The data underlying this article were provided by S&P Global Market Intelligence Data through Wharton Research Data Services (WRDS). Data will be shared on request to the corresponding author with permission of data providers.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

Appendix

Table A.1. Variable definitions

Variable	Definition
Δlog(Sales)	Change in the log of sales from supplier i to client j between years $t-1$ and t (Compustat).
ΔDistance 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 (DLC + DLTT)/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	HP Index (repeat-sales Index) in county of firm's main headquarters (Federal Housing Finance Agency).
ΔHP	Change in HP Index in percentage.
ΔHP < 0	Dummy variable that takes a value of one if ΔHP is negative, and zero otherwise.
RE	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 RE assets in 1993, scaled by total assets, inflated by the change in HPs 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 AT + CSHO × PRCC_F – [AT – (LT + PSTKL) + TXDITC]/AT).
Distance	Distance between the counties of the supplier's headquarters and the client's headquarter in miles.
Market Share	Sales divided by total industry (three-digit SIC) sales.
Number of Suppliers	Number of firms in each industry (three-digit SIC).
Lerner Index	Median net margin in the industry (three-digit SIC).
Net Margin	Net income to sales (Compustat NI/SALE).
R&D	Research and development (R&D) expenditures divided by total assets (Compustat XRD/AT).

(continued)

Table A.1. Continued

Variable	Definition
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).

References

Adelino, M., Schoar, A., and Severino, F. (2015): House prices, collateral, and self-employment, *Journal of Financial Economics* 117, 288–306.

Almeida, H., Carvalho, D., and Kim, T. (2018) Understanding the credit multiplier: The working capital channel, Working paper, University of Illinois Urbana-Champaign.

Almeida, H. and Philippon, T. (2007): The risk-adjusted cost of financial distress, *Journal of Finance* 62, 2557–2586.

Andrade, G. and Kaplan, S. (1998): How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed, *Journal of Finance* 53, 1443–1493.

Baghai, R., Silva, R., Thell, V., and Vig, V. (2021): Talent in distressed firms: investigating the labor costs of financial distress, *Journal of Finance* 76, 2907–2961.

Banerjee, A. and Duflo, E. (2014): Do firms want to borrow more? Testing credit constraints using a directed lending program, *Review of Economic Studies* 81, 572–607.

Banerjee, S., Dasgupta, S., and Kim, Y. (2008): Buyer–supplier relationships and the stakeholder theory of capital structure, *Journal of Finance* 63, 2507–2552.

Barrot, J. and Sauvagnat, J. (2016): Input specificity and the propagation of idiosyncratic shocks in production networks, *Quarterly Journal of Economics* 131, 1543–1592.

Bernanke, B. and Gertler, M. (1989): Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14–31.

Bernanke, B., Gertler, M., and Gilchrist, S. (1999) The financial accelerator in a quantitative business cycle framework, in: J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, Elsevier. pp. 1341–1393.

Bharath, S. and Shumway, T. (2008): Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339–1369.

Bolton, P. and Scharfstein, D. (1990): A theory of predation based on agency problems in financial contracting, *American Economic Review* 80, 93–106.

Brown, J. and Matsa, D. (2016): Boarding a sinking ship? An investigation of job applications to distressed firms, *Journal of Finance* 71, 507–550.
Campello, M., Connolly, R., Kankanhalli, G., and Steiner, E. (2022): Do real estate values boost corporate borrowing? Evidence from contract-level data, *Journal of Financial Economics* 144, 611–644.
Chaney, T., Sraer, D., and Thesmar, D. (2012): The collateral channel: how real estate shocks affect corporate investment, *American Economic Review* 102, 2381–2409.
Chevalier, J. and Scharfstein, D. (1996): Capital-market imperfections and countercyclical markups: theory and evidence, *American Economic Review* 86, 703–725.
Cohn, J. B. and Wardlaw, M. I. (2016): Financing constraints and workplace safety, *Journal of Finance* 71, 2017–2058.
Cvijanović, D. (2014): Real estate prices and firm capital structure, *Review of Financial Studies* 27, 2690–2735.
Daripa, A. and Nilsen, J. (2011): Ensuring sales: a theory of inter-firm credit, *American Economic Journal: Microeconomics* 3, 245279.
Denis, D. and Denis, D. (1995): Performance changes following top management dismissals, *Journal of Finance* 50, 1029–1057.
Dougal, C., Parsons, C., and Titman, S. (2015): Urban vibrancy and corporate growth, *Journal of Finance* 70, 163–210.
Dougal, C., Parsons, C., and Titman, S. (2022): The geography of value creation, *Review of Financial Studies* 35, 4201–4248.
Elkamhi, R., Ericsson, J., and Parsons, C. A. (2012): The cost and timing of financial distress, *Journal of Financial Economics* 105, 62–81.
Ellison, G., Glaeser, E., and Kerr, W. (2010): What causes industry agglomeration? Evidence from coagglomeration patterns, *American Economic Review* 100, 1195–1213.
Fudenberg, D. and Tirole, J. (1986): A "signal-jamming" theory of predation, *RAND Journal of Economics* 17, 366–376.
Gan, J. (2007): Collateral, debt capacity, and corporate investment: evidence from a natural experiment, *Journal of Financial Economics* 85, 709–734.
Garcia, D. and Norli, O. (2012): Geographic dispersion and stock returns, *Journal of Financial Economics* 106, 547–565.
Gilchrist, S., Schoenle, R., Sim, J., and Zakrajsek, E. (2017): Inflation dynamics during the financial crisis, *American Economic Review* 107, 785–823.
Giroud, X. and Mueller, H. (2017): Firm leverage, consumer demand, and employment losses during the great recession, *Quarterly Journal of Economics* 132, 271–316.
Hadlock, C., and Pierce, J. (2010): New evidence on measuring financial constraints: moving beyond the KZ Index, *Review of Financial Studies* 23, 1909–1940.
Hanka, G. (1998): Debt and the terms of employment, *Journal of Financial Economics* 48, 245–282.
Hart, O. and Moore, J. (1994): A theory of debt based on the inalienability of human capital, *Quarterly Journal of Economics* 109, 841–879.
Hortacsu, A., Matvos, G., Syverson, C., and Venkataraman, S. (2013): Indirect costs of financial distress in durable goods industries: the case of auto manufacturers, *Review of Financial Studies* 26, 1248–1290.
Imbens, G. and Wooldridge, J. (2009): Recent developments in the econometrics of program evaluation, *Journal of Economic Literature* 47, 5–86.
Kale, J. R. and Shahrur, H. (2007): Corporate capital structure and the characteristics of suppliers and customers, *Journal of Financial Economics* 83, 321–365.
Kaplan, S. and Zingales, L. (1997): Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112, 169–215.

Khwaja, A. and Mian, A. (2008): Tracing the impact of bank liquidity shocks: evidence from an emerging market, *American Economic Review* 98, 1413–1442.
Kim, R. (2018): The effect of the credit crunch on output price dynamics: the corporate inventory and liquidity management channel, Working paper, Columbia University.
Kini, O., Shenoy, J., and Subramaniam, V. (2017): Impact of financial leverage on the incidence and severity of product failures: evidence from product recall, *Review of Financial Studies* 30, 790–1829.
Kiyotaki, N. and Moore, J. (1997): Credit cycles, *Journal of Political Economy* 105, 211–248.
Klemperer, P. (1987): Markets with consumer switching costs, *Quarterly Journal of Economics* 102, 375–394.
Korteweg, A. (2010): The Net Benefits to Leverage, *Journal of Finance* 65, 2137–2170.
Lian, C. and Ma, Y. (2021): Anatomy of corporate borrowing constraints, *Quarterly Journal of Economics* 136, 229–291.
Maksimovic, V. and Titman, S. (1991): Financial policy and reputation for product quality, *Review of Financial Studies* 4, 175–200.
Matsa, D. (2011): Running on empty? Financial leverage and product quality in the supermarket industry, *American Economic Journal: Microeconomics* 3, 137–173.
Merton, R. (1974): On the pricing of corporate debt: the risk structure of interest rates, *Journal of Finance* 29, 449–470.
Mian, A. and Sufi, A. (2011): House prices, home equity-based borrowing, and the US household leverage crisis, *American Economic Review* 101, 2132–2156.
Mian, A. and Sufi, A. (2014): What explains the 2007–2009 drop in employment? *Econometrica* 82, 2197–2223.
Modigliani, F. and Miller, M. (1958): The cost of capital, corporation finance, and the theory of investment, *American Economic Review* 48, 261–297.
Nocke, V. and Thanassoulis, J. (2014): Vertical relations under credit constraints, *Journal of the European Economic Association* 12, 337–367.
Opler, T. and Titman, S. (1993): The determinants of leveraged buyout activity: free cash flow vs, *Financial Distress Costs, Journal of Finance* 48, 1985–1999.
Opler, T. and Titman, S. (1994): Financial distress and corporate performance, *Journal of Finance* 49, 1015–1040.
Paravisini, D., Rappoport, V., and Schnabl, P. (2020): Specialization in bank lending: evidence from exporting firms, Working paper, London School of Economics and Political Science.
Rampini, A. and Viswanathan, S. (2020): Collateral and secured debt, Working paper, Duke University.
Saiz, A. (2010): The geographic determinants of housing supply, *Quarterly Journal of Economics* 125, 1253–1296.
Sautner, Z. and Vladimirov, V. (2018): Indirect costs of financial distress and bankruptcy law: evidence from trade credit and sales, *Review of Finance* 22, 1667–1704.
Schmalz, M., Sraer, D., and Thesmar, D. (2017): Housing collateral and entrepreneurship, *Journal of Finance* 72, 99–132.
Titman, S. (1984): The effect of capital structure on a firm's liquidation decision, *Journal of Financial Economics* 13, 137–151.
Titman, S. and Tsyplakov, S. (2007): A dynamic model of optimal capital structure, *Review of Finance* 11, 401–451.