Internet Appendix for "Counterparty Risk: Implications for Network Linkages and Asset Prices"

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IA.1 Variable description and construction

Accruals. In line with Sloan (1996) each firm's total accruals is measured as the annual change in noncash working capital (NCWC) minus the firm's depreciation and amortization expense (Compustat Annual item DP) for the most recent reporting year. Total accruals are scaled by each firm's average total assets (Compustat item AT) reported for the previous two fiscal years. Noncash working capital is the change in current assets (Compustat Annual item ACT) minus the change in cash and short-term investments (Compustat Annual item CHE), minus the change in current liabilities (Compustat Annual item LCT), plus the change in debt included in current liabilities (Compustat Annual item DLC), plus the change in income taxes payable (Compustat Annual item TXP). If either Compustat item DLC or Compustat item TXP is missing, then its value is set to zero.

Asset growth. Asset growth is calculated as the year-on-year annual growth rate of total assets (Compustat Annual item AT) betweens years $t-1$ and t. The book value of assets in each year is deflated by the GDP deflator and expressed in terms of 2009 dollars.

Book-to-market (B/M). A firm's book-to-market ratio is constructed by following Daniel and Titman (2006). Book equity is defined as shareholders' equity minus the value of preferred stock. If available, shareholders' equity is set equal to stockholders' equity (Compustat Annual item SEQ). If stockholders' equity is missing, then common equity (Compustat Annual item CEQ) plus the par value of preferred stock (Compustat Annual item PSTK) is used instead. If neither of the two previous definitions of stockholders' equity can be constructed, then shareholders' equity is the difference between total assets (Compustat Annual item AT) and total liabilities (Compustat Annual item LT).

For the value of preferred stock we use the redemption value (Compustat Annual item PSTKRV), the liquidating value (Compustat Annual item PSTKL), or the carrying value (Compustat Annual item PSTK), in that order of preference. We also add the value of deferred taxes and investment tax credits (Compustat Annual item TXDITC) to, and subtract the value of post-retirement benefits (Compustat Annual item PRBA) from, the value of book equity if either variable is available. Finally, the book value of equity in the fiscal year ending in calendar year $t-1$ is divided by the market value of common equity from December of year $t-1$.

Cash-to-assets (Cash / assets). Cash-to-assets is computed as cash and cash equivalents (Compustat Annual item CHE) divided by total assets (Compustat Annual item AT).

Cash conversion cycle. We construct a firm's cash conversion cycle (CCC) as the 365 times the sum of ratios of inventories outstanding, receivables outstanding, and payables outstanding. The inventory outstanding ratio is defined as the average value of inventories (Computstant Annual item INVT) in years $t-1$ and t divided by the cost of goods sold (Compustat Annual item COGS). The receivables outstanding ratio is defined as the average value of accounts receivable (Computstant Annual item RECT) in years $t-1$ and t divided by sales (Compustat Annual item SALE). The payables outstanding ratio is defined as the average value of accounts payable (Compustat Annual item AP) in years $t-1$ and t divided by COGS. This definition of CCC is consistent with Wang (2019), but applied to the Compustat Annual dataset.

Debt covenants. Debt covenants is an indicator variable equal to one if a loan includes a financial covenant, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Data on financial constraints are obtained from DealScan.

Debt covenants (Customer). We compute the proportion of debt covenants included in private debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2020, we identify the set of customers associated with each supplier. Debt covenants is an indicator variable equal to one if a loan includes a financial covenant, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Finally, we compute the average debt covenant indicator across all of the customers associated with a given supplier.

Duration. The average duration (in months) of each supplier firm with its customers is computed using the FactSet Revere database, which contains monthly data on the links between supplier-customer pairs between April 2003 and December 2020, as follows. First, the FactSet Revere database is linked to CRSP so that only customers and suppliers that can be associated with a CRSP permno are retained. Second, for each supplier with more than one customer in each month t beginning in April 2003, the set of customers associated with this supplier is identified, and the number of months each supplier-customer link lasts going forward is computed. Finally, the equal-weighted average of the duration of each customer-supplier link is calculated to obtain the typical duration associated with each supplier at time t. This procedure is then repeated for all suppliers and each month.

Future sales growth. The cumulative future sales growth rate of a firm is computed as the total growth rate of sales (Compustat Annual item SALE) between years t and $t+2$. The value of sales in each year is deflated by the GDP deflator and expressed in terms of 2009 dollars.

Hadlock-Pierce index of financial constraints. Following Hadlock and Pierce (2010), the

Hadlock-Pierce index of financial constraints (SA) is based on the size and age of each firm in the Compustat universe. The size of each firm is measured as the natural logarithm of the real value of book assets, expressed in terms of 2009 dollars. The real value of book assets is capped at \$4.5 billion, meaning that firms with more than \$4.5 billion worth of real total assets have their value of real total assets set to \$4.5 billion. Age is measured the number of years the firm has been listed in Compustat with a non-missing stock price, and is capped at 37 years. Finally, the SA index of financial constraints for firm i in fiscal year t is $SA_{i,t} = -0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.040 \times \text{Age}_{i,t}$.

HHI (Customers). We compute the Herfindahl–Hirschman Index (HHI) index of the set of customers associated with each supplier using the FactSet Revere database. Specifically, in each month between April 2003 and December 2020, we record the customers associated with each supplier. Then, using the total sales of each customer, we compute the sale HHI of its customers.

Idiosyncratic return volatility (IVOL). Idiosyncratic volatility is computed in accordance with Ang et al. (2006). At the end of month t, a firm's idiosyncratic volatility over the past month is obtained by regressing its daily excess returns on the daily Fama and French (1993) factors, provided there are at least 15 valid daily returns in the month of interest. Idiosyncratic volatility is then defined as the standard deviation of the residuals from the aforementioned regression.

IVOL (Customer). We compute the idiosyncratic return volatility of each supplier's customers using the FactSet Revere database. Specifically, in each month between April 2003 and December 2020, we identify the set of customers associated with each supplier. Next, for each customer, we compute its idiosyncratic return volatility (IVOL) in accordance with Ang et al. (2006) (see above). Finally, we compute the sales-weighted average IVOL across all the customers associated with the supplier.

Inventory growth. Inventory growth is computed as the annual growth rate of inventories (Compustat Annual item INVT) between years $t-1$ and t.

Leverage. The leverage ratio is calculated as the sum of total long-term debt (Compustat Annual item DLTT) and debt in current liabilities (Compustat Annual item DLC) divided by total assets (Compustat item AT).

Loan spread. Loan spread is calculated as the total annual spread on a given loan over LIBOR, net of upfront fees, expressed as a percentage. If a firm has more than one loan outstanding at a given point in time, the variable is averaged across the firm's loans. Data on loan spreads are obtained from DealScan.

Loan spread (Customer). We compute the loan spread of all the private debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2020, we identify the set of customers associated with each supplier. Loan spread is calculated as the total annual spread on a given loan over LIBOR, net of upfront fees, expressed as a percentage. If a firm has more than one loan outstanding at a given point in time, the variable is averaged across the firm's loans. Finally, we compute the average loan spread across all of the customers associated with a given supplier.

Momentum. A firm's past return momentum in month t is defined as its cumulative return between months $t-11$ and $t-1$. This measure is constructed using CRSP Monthly return data that is adjusted for de-listing events.

Network (eigenvalue) centrality. In line with Ahern (2013), we define network centrality as the principal eigenvector of the monthly adjacency matrix implied by the FactSet Revere database. Using this FactSet data, we build monthly adjacency matrices of supplier-customer links by following the procedure described by Gofman, Segal, and Wu (2020).

Number of customers (Num. customers). The number of customers associated with each supplier is calculated using the FactSet Revere database, which contains monthly data on the links between supplier-customer pairs between April 2003 and December 2020, as follows. First, the FactSet Revere database is linked to CRSP so that only customers and suppliers that can be associated with a CRSP permno are retained. Second, for each supplier in each month t beginning in April 2003, the number of customers associated with this supplier is counted. This procedure is then repeated for all suppliers in each month.

O-Score. In line with Ohlson (1980), we compute the probability of bankruptcy as $0 = -0.407\ln(AT) + 6.03TLTA - 1.43WCTA + 0.076CLCA - 1.72NEG - 2.73NITA - 1.83PITL + 0.285NITWO - 0.521CHNI - 1.32$. Here, AT represents a firm's total assets (Compustat Annual item AT), $TLTA$ is defined as book leverage (Compustat Annual item DLC plus Compustat Annual item DLTT) scaled by total assets, and $WCTA$ is working capital (Compustat Annual item ATC minus Compustat Annual item LCT) scaled by total assets. $CLCA$ represents the ratio of current liabilities (Compustat Annual item LCT) divided by current assets (Compustat Annual item ACT). NEG is an indicator variable that takes on a value of one if total liabilities (Compustat Annual item LT) exceed total assets, and is zero otherwise. $NITA$ is the ratio of net income (Compustat Annual item NI) to total assets and $PITL$ is the ratio of funds provided by operations (Compustat Annual item PI) to total liabilities. $NITWO$ is an indicator variable equal to one if net income has been negative in each of the last two years, and zero otherwise. Finally, $CHNI$ is defined as the difference between net income in each of the previous two fiscal years divided by the sum of the absolute value of net income in each of the previous two fiscal years.

Operating leverage. We define a firm's operating leverage as sales (Compustat Annual item SALE) minus selling, general and administrative expenses (Compustat Annual item XSGA), scaled by sales.

Secured debt. Secured debt is an indicator variable equal to one if a loan is secured by collateral, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Data on secured debt are obtained from DealScan.

Secured debt (Customer). We compute the proportion of secured debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2020, we identify the set of customers associated with each supplier. Secured debt is an indicator variable equal to one if a loan is secured by collateral, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Finally, we compute the average secured debt indicator across all of the customers associated with a given supplier.

Size. A firm's end of month t market capitalization is computed as the firm's end of month t stock price (CRSP Monthly item PRC) multiplied by the firm's number of shares outstanding (CRSP Monthly item SHROUT).

Upstreamness. The upstreamness measure employed in this paper is based on the methodology of Antràs et al. (2012), as adopted by Gofman, Segal, and Wu (2020). We measure a firm's upstreamness by using the U.S. Bureau of Economic Analysis (BEA) input-output tables. We then use this BEA data to construct the measure of upstreamness by following the procedure described by Gofman, Segal, and Wu (2020).

Receivables to sales (R/S). Trade receivables to sales is computed as trade receivables (Compustat Annual item RECTR) divided by total sales (Compustat Annual item SALE).

Return on assets (ROA). Return on assets is computed as net income (Computat Annual item NI) divided by total assets (Compustat Annual item AT).

Total factor productivity (TFP). The firm-level estimates of TFP are drawn from Imrohoroglu and Tuzel (2014).

IA.2 Ruling out alternative mechanisms for the counterparty premium

Our model suggests that the main explanation for the counterparty premium is that high R/S firms are hedged against systematic frictions involved in the search for new customers. While we do not claim that this is the only mechanism that can rationalize the R/S spread, our model demonstrates that this mechanism is plausible and quantitatively important. Below, Section IA.2.1 reports a comprehensive examination of the characteristics of the R/S-sorted portfolios. The table helps to rule out some alternative mechanisms that may also generate a spread between low and high R/S firms. Section IA.2.2 then conducts an extensive set of portfolio double sorts that demonstrate that counterparty premium is distinct from other risk premia and spreads (e.g., the profitability premium and the momentum effect).

IA.2.1 Portfolio characteristics and alternative hypotheses

We begin by reporting a comprehensive set of CRSP/Compustat characteristics associated with the R/S-sorted portfolios. These characteristics, which are reported in Table IA.2.1, are constructed by value-weighting the firm-level characteristics of the firms assigned to each R/S portfolio on each portfolio formation date. We then compute the time-series average of these portfolio-level characteristics. In constructing these characteristics, we ensure that any accounting data used here are publicly available on the relevant portfolio formation dates.

The table shows that the R/S ratio is, by construction, increasing monotonically from a value of 0.03 for the low R/S portfolio to a value of 0.50 for the high R/S portfolio. However, the low and high R/S portfolios show no statistically significant differences in terms of key characteristics, such as size, book-to-market ratios, asset growth rates, inventory growth rates, and idiosyncratic return volatility. We use these and other characteristics reported in Table IA.2.1, along with further analyses and tables (referenced below), to rule out many alternative explanations for the counterparty premium.

Independence from related spreads. Table IA.2.1 raises the possibility that the counterparty premium may be related to the profitability premium or the momentum effect. This is because low (high) R/S firms tend to be relatively profitable (unprofitable) firms with high (low) stock return momentum. Each of these potentially confounding effects related to profitability and momentum is well established in the context of the asset-pricing literature. In Section IA.2.2 we demonstrate that the counterparty premium is distinct from the profitability premium and the momentum effect. The R/S spread remains significant after controlling for these characteristics via portfolio double-sort procedures and Fama-Macbeth regressions (reported in Table IA.6.20). Using a similar methodology, Section IA.2.2 also shows that differences in working capital (e.g., the accruals effect) and cash holdings, among other characteristics, cannot explain the R/S spread either.

Ex-ante industry-level differences. Since different industries have different business models and levels of competition, firms in some industries may rely on trade credit more heavily than others. As a result, sorting firms on the basis of R/S may capture ex-ante heterogeneity in industry affiliation. The fact that we report our key asset-pricing tests using *industry-adjusted* R/S ratios already goes a long way towards alleviating this concern, as this industry adjustment has little effect on our results (recall, for example, Panel B in Table 1).

We further confirm that ex-ante industry-level differences are not driving our results by performing an additional test. Specifically, we conduct a conditional double sort analysis in which we construct the R/S spread *within* each Fama-French 10 industry group. We sort firms within each industry into three portfolios based on each firm's R/S in an identical fashion to the benchmark analysis. Table IA.6.19 shows that the R/S spread is positive within all but one industry. Moreover, while the R/S spread is not statistically within each industry, we reject the null hypothesis that the counterparty premium is zero across all industries at better than the 1% level. The simple average of the industry-level R/S spread is 0.60% per month, which is 95% of the magnitude of the unconditional R/S spread reported in Table 1. Thus, the counterparty premium is *not* driven by ex-ante differences across industries.

Differential lending capacity. A high R/S ratio may reflect a firm with more capacity to extend trade credit. For instance, firms with lower financial constraints may not only be safer, but may also extend more trade credit. In contrast to this logic, Table IA.2.1 shows no difference between low and high R/S firms in terms of the Hadlock and Pierce (2010) financial constraints index. The table not only also shows that low R/S firms have lower leverage, but also shows no differences between low and high R/S firms in terms of their loan spreads, likelihoods of borrowing on a secured basis, or proportions of debts that include covenants. Table IA.2.4 in the next section also shows that financial distress cannot explain the counterparty premium either, as we document a quantitatively large and statistically significant counterparty premium after controlling for the Ohlson (1980) measure of distress. Collectively, these facts eliminate leverage as a potential explanation for the spread, and also suggests that net of liabilities, low R/S firms may actually possess a larger lending capacity.

Investment-trade credit tradeoff. If firms choose to extend less trade credit when they are endowed with more growth opportunities, then they may have to forgo investment opportunities if their trade credit provision leads to insufficient internal funds. If the trade-off between investment projects and receivables is binding, low R/S firms should be riskier and also exhibit lower asset growth rates. Opposite to this rationale, there is no statistical difference in asset growth between the extreme R/S-sorted portfolios. Furthermore, there is no difference between the R/S-sorted portfolios in terms of idiosyncratic volatility, a proxy for the existence of growth options (Ai and Kiku (2015)).[1]

Trade credit factoring. The anomalous relation between trade credit and risk premia, and the explanation that we propose for this relation, is not confounded by the fact that some firms may sell their trade credit to a third party. First, any trade credit that has been factored or sold to another party is not reported on a supplier's balance sheet. Second, the ability to factor trade credit may

[1] Murfin and Njoroge (2014) show that a trade-off exists between offering trade credit and investment for small supplier firms. This trade-off is more prominent during periods of tight bank credit, such as economic downturns. However, most of these small supplier firms are not publicly listed.

reduce the risk of high R/S firms by decreasing their exposure to shocks that impact their customers. Relatedly, Costello (2019) shows that using collateral can also mitigate suppliers' concerns for the customer's credit risk. If the underlying source of risk behind the counterparty premium were a pure "default" risk, and if selling trade credit potentially eliminates this risk, then this would result in a close to zero return spread between high and low R/S firms.[2] Factoring does not explain why high R/S firms earn a *lower* risk premium. Third, once trade credit is extended, the customer's liquidity is improved regardless of whether the supplier then sells the trade credit to another party. In case of a customer default, the supplier may not suffer a loss if trade credit is factored, but it must still engage in a search for a new customer. These inevitable search frictions render low R/S firms riskier.

Cash flow smoothing mechanism. A firm experiencing high sales today but anticipating low sales in the future may attempt to smooth its profits through its working capital. In contrast to this hypothesis, we do not find evidence that lower trade credit is driven by this type of smoothing mechanism. First, we find that firms with higher R/S today do not have lower future sales. The cumulative sales growth from the beginning of the portfolio formation period to the end of the holding period is larger for high R/S firms, although the difference is insignificant. This suggests that the incentive of high R/S firms to engage in smoothing is small. Second, firms may also smooth their profits by holding higher inventories. Belo and Lin (2012) and Jones and Tuzel (2013) show that higher inventory growth firms have lower expected returns. However, we find no significant difference in inventory growth rates between the R/S-sorted portfolios. This is another indication that differences R/S are not primarily driven by smoothing incentives.

Bargaining and market power. The allocation of trade credit could be determined via bargaining between suppliers and customers. If a supplier (customer) has less (more) vertical bargaining power, then the equilibrium R/S would be higher. However, there are two indications that a bargaining story is unlikely to explain the empirical findings. First, Table 4 shows that low and high R/S firms do not differ in terms of eigenvalue centrality, a common measure of market power that is associated with risk premia (see Ahern (2013)). Moreover, Table IA.6.24 conducts a portfolio double sort showing that the counterparty premium remains significant across centrality-sorted portfolios. Likewise, customer concentration is also associated with bargaining power, but the same table shows no difference in the HHI of customers associated with low and high R/S suppliers. That is, the customers of high R/S firms are not more concentrated than low R/S firms.

Heterogeneity in trade credit terms. There is no publicly available data that allows us to observe the exact terms under which a supplier extends trade credit to customers (e.g., maturity and interest rate). Nonetheless, two pieces of empirical evidence suggest that potential heterogeneity in trade credit terms is not a first-order concern regarding the explanation of the counterparty premium. First, large differences in trade credit terms are likely to arise *across* industries (e.g., Ng, Smith, and Smith (1999)). However, as shown in Table IA.6.19, the counterparty premium is positive and significant *within* the majority of industries. Second, Table IA.2.1 shows that the customers of high and low R/S suppliers do not differ in regards to their costs of bank loans, or the probability that

[2] When factoring trade credit to a third party, it is common for the third party to only provide the lender with a fraction (e.g., 80%) of the value of the trade credit upfront. The lender then receives the remaining balance (net of fees) only if customers repay their obligations. This practice means that, even with factoring, the original lender may still bear a small amount of counterparty default risk.

financial covenants are included in their bank loans. As the terms of bank loans are not significantly different, the terms of trade credit are unlikely to differ. Collectively, this evidence suggests that the *level* of trade credit extended is of primary importance for understanding the counterparty risk of suppliers.

Accounts payable. Firms that extend less trade credit to their customers may also receive less trade credit from their suppliers. To examine whether there is a risk premium associated with the amount of trade credit received, we sort the cross-section of firms into portfolio based on the ratio of accounts payable to the cost of goods sold (i.e., $AP/COGS$). The portfolio formation procedure follows that described in Section 1.2.1, and the results of this exercise are reported in Table IA.6.22. The table shows that sorting firms into portfolios on the basis of $AP/COGS$ yields an economically and statistically insignificant spread of about 0.21% per month. Thus, we focus on the R/S measure in this study.

Table IA.2.1: Accounting and return-related characteristics of the R/S portfolios
The table shows the value-weighted characteristics of portfolios sorted on the trade receivables to sales (R/S) ratio. All data is annual and is recorded at the end of each June from 1978 to 2020. Details on the construction of each variable are provided in Section IA.1 of the Online Appendix. The column Diff(L-H) refers to the difference between the average characteristics of the low and high R/S portfolios, and t(Diff) is the Newey and West (1987) t-statistic associated with this difference.

	Low (L)	Medium	High (H)	Diff(L-H)	t(Diff)
R/S	0.03	0.14	0.50	-0.48	
ln(ME)	8.89	9.17	8.73	0.16	(0.85)
ln(BM)	-1.18	-1.04	-1.09	-0.09	(-1.22)
Cash / assets	0.10	0.13	0.12	-0.02	(-1.70)
Leverage	0.25	0.22	0.34	-0.09	(-5.29)
Hadlock-Pierce	-3.99	-4.09	-4.01	0.02	(0.25)
Asset growth	0.16	0.13	0.14	0.01	(0.47)
Inventory growth	0.13	0.12	0.17	-0.04	(-1.22)
ROA	0.08	0.08	0.03	0.05	(9.14)
IVOL	1.44	1.17	1.34	0.10	(0.94)
Momentum	0.22	0.20	0.17	0.05	(2.15)
Future sales growth	0.23	0.16	0.20	0.03	(0.62)
Loan spread	88.12	73.68	109.02	-19.59	(-1.47)
Secured debt	0.16	0.10	0.23	-0.06	(-0.75)
Debt covenants	0.21	0.22	0.31	-0.10	(-1.25)

IA.2.2 Independence from other risk premia and spreads

This section conducts portfolio double sorts to demonstrate that the counterparty premium is distinct from the profitability premium and the momentum effect, as well as a host of other risk premia and return spreads. We implement these conditional portfolio double sorts in three steps. First, we sort the the cross-section of firms into three portfolios on the basis of a control variable (e.g., momentum) on each portfolio formation date. Second, and *within* each of the three characteristic-sorted portfolios obtained in the first step, we sort the cross-section of firms on the basis of R/S. Finally, we compute the value-weighted returns of each of the nine portfolios constructed in the previous two steps, and hold these portfolios until the next portfolio formation date when all portfolios are rebalanced. This procedure allows us to assess the economic and statistical significance of the counterparty premium while keep the effects of the control variable from the first stage relatively constant.

Each set of portfolio double sorts then reports (i) the R/S spread and its associated p-value within each of the three characteristic-sorted portfolios (e.g., the three R/S spreads obtained by holding momentum relatively constant), and (ii) the p-value from a joint test on that null hypothesis that the counterparty risk premium across all three characteristic-sorted portfolios is zero.

Moreover, Table IA.6.20 confirms the results of these portfolio double sorts using Fama-Macbeth regressions. We demonstrate that when projecting future excess returns on R/S and a host of other firm-level characteristics known to predict returns, the slope coefficient on R/S remains negative and significant.

Profitability and momentum. Table IA.2.2 verifies that the counterparty premium is distinct from the profitability premium and the momentum effect. The table reports the value-weighted returns from a conditional portfolio double sort in which the first stage sorting variable in Panel A (Panel B) is ROA (momentum). The results in Panel A show that after controlling for profitability, the counterparty premium remains positive and significant within each ROA-sorted portfolio. The counterparty premium is not only economically sizable in all three cases, but also remains statistically significant at the 1% level or better. Furthermore, the joint test on the null hypothesis that the R/S spread is zero across the three profitability-sorted portfolios is rejected at the 1% level.

Similarly, Panel B shows the counterparty premium remains positive and significant within each momentum-sorted portfolio. The magnitude of R/S spread not only exceeds 1% per month among high momentum firms, but is also statistically significant at the 1% level among medium and low momentum firms. The null hypothesis that the counterparty premium is jointly zero across the three momentum-sorted portfolios is also rejected at the 1% level.

Accruals and working capital. Given the close association between trade credit and other forms of working capital, we confirm that the counterparty premium does not simply reflect these related spreads. For instance, Sloan (1996) shows that firms with low accruals (i.e., less working capital) earn high future returns. This pattern in returns is attributed to investors overestimating the persistence of accruals when forecasting future accounting earnings. However, since trade credit is a component of current assets (and hence accruals), there is a mechanical positive relation between accruals and R/S. In light of this relation, we first show that the R/S spread survives controlling for accruals.

Panel A of Table IA.2.3 show that the R/S spread earns over 0.55% per month among medium and high accruals firms. The R/S spreads within these two accruals-sorted portfolio are each significant at the 1% level. Furthermore, a joint test shows that the counterparty premium is also significant at the 1% level across all accruals portfolios. Collectively, this evidence suggests that the accruals effect cannot explain the R/S spread.

We extend this evidence in Panel B of Table IA.2.3, which shows that the cash-conversion-cycle (CCC) from Wang (2019) cannot explain the R/S spread either. Similar to accruals, CCC combines multiple operating ratios and accounting variables (including accounts receivable) to establish a return spread that is interpreted as arising from mispricing. In contrast, we focus on the asset-pricing implications of the receivables component only, and use novel network data to show that there is a risk-based explanation for the R/S spread. Nonetheless, Panel B shows that the R/S spread is economically and statistically significant within two of the three CCC-sorted portfolios. The counterparty premium is also jointly significant across the three CCC-sorted portfolios, with a p-value of 0.01. This highlights that CCC does not drive the R/S spread.

Precautionary savings and the distress premium. Table IA.2.1 shows that low R/S firms hold slightly less cash than high R/S firms. First, we note that this difference cannot account for the counterparty premium: Palazzo (2012) finds that firms with more cash holdings are riskier, and have higher expected returns, whereas we find that high R/S firms (who hold more cash) have lower expected returns. Second, Panel A of Table IA.2.4 controls for the cash-to-asset ratio of each firm, and shows that an economically sizable and statistically significant R/S spread arises within each portfolio. The joint test also strongly rejects ($p < 0.01$) the null hypothesis that the R/S spread is zero across the three portfolios. Thus, the R/S spread persists regardless of firms' cash holdings.

In a related test, Panel B of Table IA.2.4 also further confirms that the counterparty premium is materially unrelated to the distress premium. As we discuss in Section 1.2.2, we would expect high R/S firms to earn higher stock returns if distress risk were the driver of the counterparty premium. This is because these firms extend more trade credit, and are consequently more exposed to the adverse shocks that weaken the financial conditions of their customers. However, the sign of the counterparty is clearly inconsistent with this narrative, as high R/S firms earn lower stock returns. Nonetheless, to completely rule out the distress premium as a driver of the counterparty premium, we perform a portfolio double sort. The results in Panel B show that the R/S spread is highly significant with and across the distress-sorted portfolios.

Table IA.2.2: Controlling for profitability and momentum: double-sort analysis
The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) in Panel A (Panel B) is a firm's ROA (momentum), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the control variable using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the control variable in the fiscal year ending in calendar year $t-1$. Second, within each characteristic-sorted portfolio, we further sort firms into three additional portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning for July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. The last two rows of each panel show the R/S spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three characteristic-sorted portfolios is zero. The sample period is from July 1978 to December 2020.

		Panel A: Controlling for ROA		
	Low ROA	Medium	High ROA	
Low R/S	0.88	1.26	1.31	
Medium	0.14	1.11	1.16	
High R/S	-0.61	0.77	0.80	
Spread	1.49	0.49	0.51	Joint test
(L-H)	($p = 0.01$)	($p = 0.00$)	($p = 0.03$)	($p = 0.00$)
		Panel B: Controlling for momentum		
	Low MOM	Medium	High MOM	
Low R/S	0.87	1.23	1.35	
Medium	0.78	1.10	1.39	
High R/S	-0.10	0.71	0.83	
Spread	0.97	0.52	0.51	Joint test
(L-H)	($p = 0.02$)	($p = 0.00$)	($p = 0.06$)	($p = 0.01$)

Table IA.2.3: Controlling for accruals and cash conversion cycle: double-sort analysis

The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) in Panel A (Panel B) is a firm's total accruals (cash conversion cycle, or CCC), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the control variable using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the control variable in the fiscal year ending in calendar year $t-1$. Second, within each characteristic-sorted portfolio, we further sort firms into three additional portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning for July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. The last two rows of each panel show the R/S spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three characteristic-sorted portfolios is zero. The sample period is from July 1978 to December 2020.

Panel A: Controlling for accruals				
	Low Accruals	Medium	High Accruals	
Low R/S	1.68	1.28	1.28	
Medium	1.26	1.12	0.86	
High R/S	1.06	0.71	0.55	
Spread	0.62	0.57	0.73	Joint test
(L-H)	($p = 0.10$)	($p = 0.00$)	($p = 0.02$)	($p = 0.01$)
Panel B: Controlling for cash conversion cycle				
	Low CCC	Medium	High CCC	
Low R/S	1.44	1.24	1.42	
Medium	1.01	1.13	1.01	
High R/S	1.00	0.61	0.77	
Spread	0.44	0.64	0.65	Joint test
(L-H)	($p = 0.17$)	($p = 0.00$)	($p = 0.04$)	($p = 0.01$)

Table IA.2.4: Controlling for precautionary savings and distress risk: double-sort analysis
The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) in Panel A (Panel B) is a firm's cash-to-asset (Ohlson (1980) O-Score), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the control variable using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the control variable in the fiscal year ending in calendar year $t-1$. Second, within each characteristic-sorted portfolio, we further sort firms into three additional portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning for July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. The last two rows of each panel show the R/S spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three characteristic-sorted portfolios is zero. The sample period is from July 1978 to December 2020.

	Panel A: Controlling for cash-to-assets			
	Low Cash/AT	Medium	High Cash/AT	
Low R/S	1.45	1.24	1.10	
Medium	0.90	1.13	1.40	
High R/S	0.71	0.69	0.42	
Spread	0.74	0.55	0.67	Joint test
(L-H)	($p = 0.01$)	($p = 0.00$)	($p = 0.05$)	($p = 0.00$)
	Panel B: Controlling for O-score			
	Low O-score	Medium	High O-score	
Low R/S	1.02	1.29	0.86	
Medium	1.15	1.15	0.54	
High R/S	0.76	0.67	-0.30	
Spread	0.26	0.62	1.16	Joint test
(L-H)	($p = 0.17$)	($p = 0.00$)	($p = 0.01$)	($p = 0.00$)

IA.3 Link duration and trade credit: macro-level evidence

The micro-level evidence in Section 1.3.2 shows that firm-level R/S positively predicts the future duration of existing links with customers. Aggregating this result from the firm-level to the macro-level suggests that the average level of R/S should positively predict the density of the production network, as more existing relationships are expected to remain alive in the future. We test this conjecture by projecting the future density of the production network on the average level of R/S across all firms while controlling for the state of the business cycle

$$Density_{t+k} = const + \beta_{rs}\overline{R/S}_t + \beta_d Density_t + \beta_{IP}\Delta IP_t + \beta_{TFP}TFP_t + \beta_{DEF}DEF_t + \eta_t. \quad (1)$$

Here, $Density_t$ is the density of the production network in quarter t, defined as the ratio of observed-to-potential links in the network, [3] ΔIP_t is the quarterly log-growth rate of the aggregate industrial

[3] In a directed network of N firms, the number of possible links is given by $N(N-1)/2$. The results of projection (1) are unchanged if we define the number of possible links as $N^2 - N$ (unrestricted).

production index, TFP_t is the utilization-adjusted TFP measure from Fernald (2012), DEF_t is the level of the Moody's corporate default spread, and $\overline{R/S}_t$ is the average R/S ratio across all firms at time t. We normalize each independent variable by its unconditional standard deviation and, for ease of interpretation, divide each slope coefficient by the unconditional mean of network density. The results are reported in Table IA.3.5.

The results show that a one standard deviation increase in aggregate $\overline{R/S}$ predicts that network density will increase by between 3% to 9% relative to its mean (depending on the set of control variables) over the next one to four quarters. Moreover, the predictive power of the aggregate R/S ratio for explaining the future density of the production network lasts for roughly eight quarters. The slope coefficients associated with the aggregate $\overline{R/S}$ ratio are both economically sizable and statistically significant across these forecast horizons, and the results show that the explanatory power of aggregate $\overline{R/S}$ is *incremental* to that of current network density.

Table IA.3.5: Predicting the production network's density

The table reports the results of time-series regressions that predict the density of links in the production network. Specifically, the projection we estimate is given by equation (1), where $Density_{t+k}$ is the density of the network at time $t+k$, IP_t is the quarterly log-growth rate of industrial production, and $\overline{R/S}_t$ is the equal-weighted average R/S ratio across all firms at time t. We measure $Density_{t+k}$ as the ratio of observed links in the production network at time $t+k$ divided by the maximum potential number of links at the same point in time. Each independent variable is scaled by its standard deviation, and for ease of interpretation, we divide each slope coefficient by the unconditional mean of the density measure. We consider forecast horizons (k) of one, three, five, and seven quarters ahead. Newey and West (1987) robust t-statistic are reported in parentheses, and the time period for the analysis ranges from January 2004 to December 2020.

	1Q ahead		4Q ahead		8Q ahead		12Q ahead	
$\overline{R/S}$	0.09	0.03	0.09	0.03	0.09	0.05	0.07	0.04
	(8.00)	(4.60)	(6.56)	(2.52)	(3.84)	(2.26)	(2.05)	(1.14)
Density		0.07		0.07		0.04		0.04
		(9.62)		(6.25)		(1.76)		(1.52)
IP		0.01		-0.00		-0.00		0.04
		(1.29)		(-0.10)		(-0.15)		(1.34)
TFP		-0.01		-0.01		-0.02		-0.00
		(-1.44)		(-0.53)		(-0.95)		(-0.16)
DEF		-0.00		0.00		-0.02		-0.02
		(-0.24)		(0.31)		(-0.81)		(-0.67)
R^2	0.56	0.86	0.39	0.65	0.27	0.34	0.11	0.21

IA.4 Discussion of the model's assumptions and model extensions

In this section we explore the model's robustness to some alternative assumptions. We first document that the model's implications are materially unchanged if suppliers are assumed to operate downstream or upstream, or have multiple customers. Next, we show that the counterparty premium is amplified by introducing either the strategic termination of links or persistence in the quality of customers, but the premium is somewhat attenuated by introducing customer-independent idiosyncratic productivity shocks. Nonetheless, in all alterations, the model-implied counterparty premium is well within the data's confidence interval.

IA.4.1 Counterparty premium within production layers

The real economy features suppliers and customers that are organized in a complex production network. However, in the interest of tractability, our model focuses on the returns of suppliers with low versus high R/S only. This is equivalent to assuming that all firms in the model operate within the same layer of the production network, and have the same distances from final consumers in the supply chain (i.e., a fixed upstreamness). Thus, the model-implied counterparty premium can be interpreted as the average R/S spread within each production layer.

To ensure that our model is tightly linked to the data, Table IA.6.23 shows the magnitude of the counterparty premium within each layer of the production network. We estimate these magnitudes using a double-sort analysis. We first sort firms into portfolios based on their upstreamness measure, as in Antràs et al. (2012) and Gofman, Segal, and Wu (2020). Then, within each upstreamness-sorted portfolio, we sort firms on the basis of R/S. The table shows that the counterparty premium is positive and statistically significant within each layer of the production network (both downstream and upstream). The average R/S spread across the low, medium and high upstreamness-sorted portfolios is 0.45% per month, or about 5.4% per annum, which is very close to the model-implied counterparty premium.

IA.4.2 Number of customers

Our model assumes that each supplier is matched with only one customer, while a in the data supplier can have multiple customers. There are two reasons for this modeling choice. First, Table 4 shows that there is no difference in customer concentration between low and high R/S firms. Consequently, customer diversification does not play a pivotal role in explaining the results. Moreover, Table IA.6.21 in the Online Appendix shows that there is no return spread between suppliers that have few versus many customers. Because heterogeneity in the number of customers is unrelated to firms' risk premia, we abstract from this type of heterogeneity in the model.

Second, the single customer of each supplier in the model can be viewed as a "representative" customer. Untabulated results confirm that a model featuring multiple customers is quantitatively equivalent to the one-customer case. This is because suppliers with multiple customers have less incentive to extend trade credit due to diversification. That is, the cost of losing any customer is smaller, leading to a lower benefit of extending trade credit. To restore the model's ability to match the mean and volatility of the firm-level R/S ratio to the data, the mean and volatility of counterparty shocks must increase. Quantitatively, increasing the risk of counterparty shocks effectively cancels out the reduction in a supplier's risk induced by customer diversification.

IA.4.3 Termination of supplier-customer links

Our model assumes that supplier-customer relationships terminate when the customer is subject to an exogenous liquidity shock that leads to a customer default. Liquidity shocks serve as a mechanism to break the link between the two firms. This is guided by theoretical and empirical research in corporate finance that highlights the role of trade credit for providing liquidity *insurance* to customers (e.g., Cunat (2006); Wilner (2000)). Nonetheless, there are two important caveats in interpreting this termination mechanism. First, customer default in our setup is not equivalent to strict "exit" events that occur, for example, following the failure to repay corporate debt. Rather, a default can be interpreted as a delay in repayment that disrupts credit lines. Similarly, the default event can capture any exogenous reason that makes the customer strategically leave its supplier (e.g., a supply chain disruption in which the customer switches to a new supplier).[4]

Second, we consider a model extension in which the supplier can *strategically* terminate the relationship with its customer. Specifically, we provide suppliers with the option to sever the link with its current customer. Upon termination, the supplier pays the rematching cost f_t, and draws a new customer with quality $C_{i,t+1}$ drawn from equation (16). Moreover, if the supplier chooses to strategically end the relationship, it does not extend any trade credit. We find that the counterparty premium in this setup increases considerably compared to the benchmark case. To see this in an extreme manner, an alternative way of modeling strategic default is by setting the parameter $\overline{p}$ to 1. Thus, by not extending any trade credit, the supplier guarantees a new customer next period. We find that when $\overline{p} = 1$, the counterparty premium rises to 12.94% per annum.

The intuition is straightforward. Assume that the supplier cannot strategically terminate the relationship with its customer. If the supplier is matched with a poor quality customer, it opts to extend no trade credit (i.e., the supplier has low R/S), and hopes that its customer will default next period (see Figure 2). In this case, suppliers that are matched with low quality customers are more likely to pay the rematching cost f_t, but the likelihood of paying f_t is less than one. On the other hand, if the supplier is matched with a poor quality customer, and opts to strategically bail, it has to pay the rematching cost f_t with probability one. Thus, strategic defaults by suppliers increase the exposure of low R/S firms to customer search frictions, amplifying the counterparty premium.

IA.4.4 Firm-level heterogeneity

In the benchmark model, the only driver of firm-level heterogeneity is the quality of the current customer $C_{i,t}$. We do not introduce other idiosyncratic productivity shocks both for parsimony and because the parameters of other firm-specific components of productivity are not separately identified from those that govern $C_{i,t}$. Nonetheless, we show that our results are largely robust to introducing idiosyncratic productivity shocks that vary period-by-period even if the current customer is unchanged. Specifically, we augment equation (10) to include a firm-specific and customer-independent productivity shock $Z_{i,t}$. Thus,

$$Y_{i,t} = (A_t C_{i,t} Z_{i,t})^{1-\alpha} K_{i,t}^{\alpha},$$

where $\log Z_{i,t} = \rho_z \log Z_{i,t-1} + \sigma_z \varepsilon_{z,i,t}$, and $\varepsilon_{z,i,t} \sim N(0,1)$ is independent over firms and time. Following the estimate of Imrohoroglu and Tuzel (2014) we set ρ_z to 0.7. Whenever $\sigma_z > 0$, the firm-specific Solow residual varies over time even if the customer is not changed.

Let $\sigma(\log Z_{i,t})$ denote the unconditional volatility of the $\log Z_{i,t}$ process. We consider two cases: low $\sigma(\log Z_{i,t}) = 5\%$, and high $\sigma(\log Z_{i,t}) = 10\%$. We discretize the state-space for $\log Z_{i,t}$ using the Tauchen (1986) method. We find that the counterparty premium is equal to 5.42% for the low $\sigma(\log Z_{i,t})$ case, and 4.39% for high $\sigma(\log Z_{i,t})$ case. Both quantities fall within the empirical confidence interval for the premium.

Note that a more volatile $\sigma(\log Z_{i,t})$ process reduces the equilibrium counterparty premium. While

[4] In the latter case, the supplier does not lose the trade credit when the link is broken. However, this has a negligible impact on our quantitative results because the model-implied counterparty premium arises primarily from exposure to search friction, which would occur regardless of the customer's repayment.

the optimal R/S policy is still increasing in $C_{i,t}$, it is also affected by the level of idiosyncratic productivity $Z_{i,t}$ because the marginal revenue of customer quality depends positively on $Z_{i,t}$. Fixing the customer's quality, the supplier wants to hedge the customer more (less) when $Z_{i,t}$ is high (low). As a result, the correlation between $C_{i,t}$ and $r_{i,t+1}$ drops, which decreases the counterparty premium. This is because $Z_{i,t}$ makes R/S a noisy proxy for the customer's quality, and this noise attenuates the spread since the underlying source of risk depends on the customer's quality.

IA.4.5 Search and quality persistence

This section extends the benchmark model to accommodate persistence in the quality of customers, rather than assuming that the quality of a new customer is drawn from an i.i.d. pool. We highlight that this assumption is not critical to our results. We pursue this extension because it is conceivable that suppliers that are currently matched with a better quality customer will be matched with a better quality customer in the future (i.e., the firm is better at attracting new customers). This quality inertia can only increase the model-implied counterparty premium, since a firm that is matched with a high quality customer today is not only less likely to search for a new customer next period, but is also less likely to search in future periods (as future customers will also be of higher quality). Thus, customer-quality inertia makes high R/S firms even safer. To illustrate this point, we change the dynamics of $C_{i,t}$ in equation (15) such that the new customer's quality is given by

$$\log C_{i,t+1} = \rho_c \log C_{i,t} + \sigma_{c,\rho}\varepsilon_{c,i,t},$$

where $\varepsilon_{c,i,t}$ is a standard normal shock that is independent over firms and over time. Importantly, we keep the unconditional volatility of $\log C_{i,t}$ process identical to the benchmark model by re-calibrating $\sigma_{c,\rho}$ to $\sqrt{\sigma_c^2(1-\rho_c^2)}$. When ρ_c is equal to 0.1, the counterparty premium increases to 6.07% p.a. Likewise, when ρ_c is set to 0.25, the equilibrium spread climbs to 7.% p.a., matching the data's point estimate. Thus, persistence in customer quality *increases* the magnitude of the model-implied counterparty premium.

IA.5 Model Solution

Define $J(K_{it}, C_{it}, A_t, f_t)$ as the value of the firm in period t *after* the firm has gathered account receivables payments from its counterparty and/or paid the rematching cost. The value function iteration problem can be formulated equivalently as:

$$\begin{aligned} J(K_{it}, C_{it}, A_t, f_t) = \max_{r_{it+1}, K_{it+1}} \quad & \hat{D}_{it} + \Gamma(r_{it+1})\,\mathbb{E}_t\left[M_{t,t+1}\left(-f_t A_t + J(K_{it+1}, C_{it+1}, A_{t+1}, f_{t+1})\right)\right] \\ & + \left[1-\Gamma(r_{it+1})\right]\mathbb{E}_t\left[M_{t,t+1}\left(Y_{it} r_{it+1} + J(K_{it+1}, C_{it}, A_{t+1}, f_{t+1})\right)\right] \end{aligned}$$

Let $\tilde{X}_t = \frac{X_t}{A_{t-1}}$. The problem above can be re-written using covariance stationary variables as follows:

$$\begin{aligned} \tilde{J}\left(\tilde{K}_{it}, C_{it}, A_t/A_{t-1}, f_t\right) = \max_{r_{it+1}, \tilde{K}_{it+1}} \quad & \tilde{Y}_{i,t}(1-r_{it+1}) - \xi\tilde{K}_{it} - \tilde{I}_{it} - \phi\left(\tilde{I}_{it}, \tilde{K}_{it}\right)\tilde{K}_{it} \\ & + \Gamma(r_{it+1})\left(\frac{A_t}{A_{t-1}}\right)\mathbb{E}_t\left[M_{t,t+1}\left(-f_t + \tilde{J}(\tilde{K}_{it+1}, C_{it+1}, A_{t+1}/A_t, f_{t+1})\right)\right] \\ & + \left[1-\Gamma(r_{it+1})\right]\mathbb{E}_t\left[M_{t,t+1}\left(\tilde{Y}_{it} r_{it+1} + \left(\frac{A_t}{A_{t-1}}\right)\tilde{J}(\tilde{K}_{it+1}, C_{it}, A_{t+1}/A_t, f_{t+1})\right)\right] \end{aligned}$$

s.t.

$$\tilde{Y}_{i,t} = \left(\frac{A_t}{A_{t-1}} C_{it}\right)^{1-\alpha} \tilde{K}_{it}^{\alpha}$$

$$\left(\frac{A_t}{A_{t-1}}\right) \tilde{K}_{it+1} = (1-\delta)\,\tilde{K}_{it} + \tilde{I}_{it}$$

$$\phi\left(\tilde{I}_{it}, \tilde{K}_{it}\right) = b\left(\frac{\tilde{I}_{it}}{\tilde{K}_{it}} - \delta\right)^2$$

$$\frac{A_{t+1}}{A_t} = \exp(\mu_a + \sigma_a \varepsilon_{t+1}^a)$$

We use value function iteration to solve the model. We discretize the Gaussian processes of f, A'/A, and C, using Tauchen (1986). The grids for the exogenous variables A'/A and C span from -3 to +3 standard deviations around their mean. The grid for C spans from -2 to +2 standard deviations around its mean. The choice of r is discretized on a grid spanning from 0 to 1. The grid for capital is logarithmic, and we make sure that in all simulated paths the choice of capital is endogenous to the grid (neither k_{min} nor k_{max} are chosen in the simulations).

IA.6 Supplemental tables and figures

Table IA.6.6: Transition matrix of constituents between R/S portfolios
The table shows the probability that a firm sorted into portfolio $i \in$ {Low, Medium, High} in year t, where i is the row index, is sorted into portfolio $j \in$ {Low, Medium, High} in year $t+1$, where j is the column index. The construction of the R/S-sorted portfolios is identical to the benchmark analysis described in Section 1.2.1. The sample spans from July 1978 to December 2020.

Portfolio in	Portfolio in year $t+1$		
year t	Low	Medium	High
Low	0.848	0.140	0.012
Medium	0.018	0.945	0.037
High	0.015	0.371	0.613

Table IA.6.7: Portfolios sorted on R/S: quintile portfolios

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that portfolio breakpoints are based on the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles of the cross-sectional distribution of R/S ratios. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.182	4.344	1.214	4.938
2	1.161	4.715	1.156	4.526
Medium	1.125	4.686	1.110	4.500
4	1.015	4.955	1.039	4.803
High R/S	0.891	5.765	0.880	5.543
Spread	0.291	3.255	0.335	2.731
(L-H)	(1.82)		(2.98)	

Table IA.6.8: Portfolios sorted on R/S: 30^{th} and 70^{th} percentile breakpoints

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that portfolio breakpoints are based on the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of R/S ratios. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.186	4.392	1.192	4.772
Medium	1.085	4.600	1.094	4.412
High R/S	0.954	5.438	0.965	5.243
Spread	0.231	2.447	0.227	2.121
(L-H)	(1.89)		(2.86)	

Table IA.6.9: Portfolios sorted on R/S: equal-weighted returns

The table reports the average equal-weighted monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.183	6.195	1.306	6.803
Medium	1.305	6.249	1.290	6.178
High R/S	0.812	7.543	0.817	7.297
Spread	0.372	3.716	0.489	2.201
(L-H)	(1.78)		(4.28)	

Table IA.6.10: Portfolios sorted on R/S: sub-sample evidence

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that the sample period underlying the results covers July 1998 to December 2020. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	0.994	4.754	1.210	6.097
Medium	0.837	4.744	0.798	4.586
High R/S	0.405	5.891	0.516	5.954
Spread	0.589	4.048	0.694	3.768
(L-H)	(2.41)		(3.33)	

Table IA.6.11: Portfolios sorted on R/S: scaling by average past sales

The table reports the average monthly returns of three portfolios sorted on receivables to sales (R/S), as well as the spread between the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that the R/S ratio is constructed by deflating trade receivables by average firm-level sales over the previous two years. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.239	4.798	1.367	5.562
Medium	1.108	4.579	1.093	4.530
High R/S	0.667	6.385	0.800	6.222
Spread	0.571	4.300	0.568	4.294
(L-H)	(2.59)		(2.96)	

Table IA.6.12: Portfolios sorted on R/S: NYSE breakpoints

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that portfolio breakpoints are based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of R/S ratios among NYSE-listed firms. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.254	4.834	1.323	5.200
Medium	1.116	4.539	1.090	4.512
High R/S	0.810	5.837	0.827	5.620
Spread	0.444	3.829	0.496	3.239
(L-H)	(2.49)		(3.87)	

Table IA.6.13: Portfolios sorted on R/S: Including $R/S_{i,t} = 0$ observations
The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that we include all observations where for firm i at time t there is no trade credit: $R/S_{i,t} = 0$. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.229	5.025	1.333	5.671
Medium	1.116	4.590	1.111	4.547
High R/S	0.623	5.984	0.755	5.877
Spread	0.606	4.038	0.578	3.781
(L-H)	(3.10)		(3.74)	

Table IA.6.14: Portfolios sorted on R/S: Including $R/S_{i,t} = 0$ observations with NYSE breakpoints
The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, and the spread between the returns of the low and high R/S portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except that (1) we include all observations where for firm i at time t there is no trade credit: $R/S_{i,t} = 0$, (2) portfolio breakpoints are based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of R/S ratios among NYSE-listed firms. Panel A reports the returns of portfolios constructed using the R/S ratio defined in equation (1), whereas Panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics, and portfolio returns span July 1978 to December 2020.

	Panel A: R/S		Panel B: R/S^{IA}	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.204	4.885	1.318	5.228
Medium	1.119	4.542	1.089	4.515
High R/S	0.812	5.835	0.835	5.610
Spread	0.393	3.739	0.483	3.216
(L-H)	(2.22)		(3.83)	

Table IA.6.15: Portfolio alphas: robustness

The table reports the results of time-series regressions of the value-weighted counterparty premium (the portfolio that buys low R/S firms and shorts high R/S firms) on a number of common risk factors. The construction of these portfolios is identical to the benchmark analysis, described in Section 1.2.1, except for the following changes. In Panel A, portfolios are constructed using the industry-adjusted R/S ratio. In Panel B, portfolio breakpoints are based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of R/S ratios among NYSE-listed firms. In Panel C, portfolios are constructed after excluding firms with a market capitalization below the 20^{th} perctile of market capitaizations across NYSE-listed firms at each point in time. In Panel D, portfolios are constructed using breakpoints based on the industry-adjusted R/S ratio among NYSE-listed firms only. Panel E repeats the analysis underlying Panel D after also exlcuding firms with a market capitalization below the 20^{th} perctile of market capitaizations across NYSE-listed firms at each point in time. In Panel F, we include $R/S_{i,t} = 0$ observations in the portfolios. Panels G and H correspond to Panels A and D, respectively, when we also include $R/S_{i,t} = 0$ observations in the portfolios. Parameter estimates are obtained by regressing monthly excess returns on each set of monthly risk factors. MKTRF is the excess return of the market portfolio. SMB and HML are the size and value factors of the Fama and French (1993), while MOM is the momentum factor of Carhart (1997). Profit. and Invest. correspond to the RMW and CMA factors (ROE and I/A factors) of the Fama and French (2015) five-factor (Hou et al. (2021) q^5-factor) model, while EG represents the expected growth factor from the q^5 model. Parentheses report Newey and West (1987) robust t-statistics. Returns span July 1978 to December 2020.

	CAPM	FF3F	FF4F	FF5F	q^5
			Panel A: Industry-adjusted R/S		
α	0.720	0.761	0.684	0.781	0.540
	(5.04)	(5.64)	(4.33)	(5.37)	(3.40)
			Panel B: NYSE breakpoints		
α	0.669	0.624	0.532	0.370	0.280
	(3.88)	(3.80)	(3.36)	(2.47)	(1.90)
			Panel C: Excluding microcaps		
α	0.732	0.696	0.614	0.483	0.392
	(3.98)	(3.90)	(3.53)	(2.85)	(2.37)
			Panel D: Industry-adjusted R/S and NYSE breakpoints		
α	0.605	0.643	0.558	0.628	0.454
	(4.96)	(5.88)	(4.63)	(5.48)	(3.66)
			Panel E: Industry-adjusted R/S and NYSE breakpoints without microcaps		
α	0.581	0.624	0.529	0.606	0.400
	(4.81)	(5.83)	(4.68)	(5.51)	(3.33)
			Panel F: Including $R/S_{i,t} = 0$ observations		
α	0.820	0.804	0.715	0.631	0.524
	(4.33)	(4.35)	(4.01)	(3.56)	(3.14)
			Panel G: Industry-adjusted R/S including $R/S_{i,t} = 0$ observations		
α	0.679	0.731	0.660	0.825	0.560
	(4.54)	(5.22)	(4.10)	(5.21)	(3.09)
			Panel H: Industry-adjusted R/S and NYSE breakpoints including $R/S_{i,t} = 0$ observations		
α	0.587	0.627	0.543	0.632	0.449
	(4.86)	(5.80)	(4.52)	(5.46)	(3.69)

Table IA.6.16: The market price of counterparty risk: Fama and French (2015) model

The table reports the estimates of the risk factor loadings associated with the Fama and French (2015) five-factor model estimated with and without the counterparty risk factor. Here, the counterparty risk factor is constructed by buying firms with high R/S ratios and selling firms with low R/S ratios. All firms underlying each R/S portfolio are value weighted. Each model is estimated by generalized methods of moments (GMM) using the moment conditions $\mathbb{E}\left[M_t r^e_{i,t}\right] = 0$, where $r^e_{i,t}$ represents the excess return of test asset i at time t and M_t denotes the stochastic discount factor. We assume that M_t is specified as $M_t = 1 - \boldsymbol{b}'\boldsymbol{f}_t - b_{CPR}CPR_t$, where $\boldsymbol{f}_t$ represents the common factors associated with the Fama and French (2015) five-factor model and CPR_t represents the counterparty risk factor. Each of these factors is demeaned, and $(\boldsymbol{b}'\ b_{CPR})'$ denotes the column vector of the risk factor loadings on the SDF that are estimated. The estimation of each asset-pricing model is conducted using the value-weighted returns of the following three sets of test assets: (1) 25 size and book-to-market portfolios, (2) the first set of test assets plus the 49 Fama-French industry portfolios, and (3) the second set of test assets plus 10 portfolios sorted on each of investment, profitability, momentum, market betas, stock issuance, accruals, variance, and residual variance. The t-statistic associated with each risk factor loading is reported in parentheses, and the mean absolute error (MAE) associated with each estimation procedure is reported in the bottom row of each panel. Monthly data spanning July 1978 to December 2020 is used to estimate each model.

Panel A: FF5F plus the counterparty risk factor						
	25 portfolios		74 portfolios		154 portfolios	
	FF5F	+CPR	FF5F	+CPR	FF5F	+CPR
b_{MKTRF}	4.494	7.564	5.145	6.651	6.000	7.186
	(2.80)	(3.47)	(4.03)	(4.98)	(5.46)	(6.45)
b_{SMB}	5.459	4.345	-0.634	-1.062	-0.275	-0.354
	(2.54)	(1.87)	(-0.34)	(-0.58)	(-0.17)	(-0.22)
b_{HML}	-0.887	-1.152	-4.377	-5.746	-7.914	-8.181
	(-0.21)	(-0.25)	(-1.63)	(-2.13)	(-4.00)	(-4.13)
b_{RMW}	13.497	6.640	4.694	1.114	8.595	5.591
	(3.32)	(1.29)	(1.73)	(0.40)	(4.76)	(2.80)
b_{CMA}	3.348	2.634	8.494	12.026	14.644	15.245
	(3.32)	(1.29)	(1.64)	(2.31)	(4.63)	(4.73)
b_{CPR}		-12.129		-4.530		-4.554
		(-2.24)		(-2.92)		(-3.41)
MAE	0.493	0.482	0.844	0.762	0.691	0.654

Table IA.6.17: Predicting the length of supplier-customer link: panel regressions

The table reports the results of panel regressions that use supplier-level characteristics to predict the average duration of each supplier's link with its customers, measured in months, in Panel A, and the probability that a supplier-customer link breaks in Panel B. The regression specification employed is denoted by $D_{s,t} = \alpha_t + \boldsymbol{\beta X'_{s,t}} + \varepsilon_{s,t}$, where the measures of duration ($D_{s,t}$) are either (1) the average future duration of each supplier's links with its customers (in Panel A), or (2) an indicator variable that identifies the situation in which the supplier-customer link breaks (in Panel B). The event that Break = 1 in the right panel corresponds to the situation in which at least half or more of a supplier's customers at time t are no longer the supplier's customers in four years time. The regression includes time fixed effects (α_t), and the vector of control variables ($\boldsymbol{X'_{s,t}}$) includes each supplier's R/S ratio, the natural logarithms of size and book-to-market ratios, the investment rate, profitability, number of customers linked to each supplier, and the average life of each supplier's links with its existing customers (looking backwards from time t). t-statistics based on clustered standard errors are reported in parentheses, and each supplier-level characteristic is standardized by dividing the characteristic by its unconditional standard deviation. The time period for the analysis ranges from June 2003 to June 2020.

	Panel A: Future duration	Panel B: Pr (Break = 1)
R/S	1.819	-0.044
	(4.12)	(-4.41)
$\ln(ME)$	0.575	0.042
	(1.61)	(6.18)
$\ln(B/M)$	-0.018	0.008
	(-0.06)	(1.01)
I/K	-0.695	0.002
	(-1.67)	(0.27)
ROA	1.530	-0.024
	(4.85)	(-5.00)
Number of customers	-0.608	-0.025
	(-2.88)	(-3.51)
Lagged duration	4.054	-0.087
	(5.00)	(-13.83)
Year FE	Yes	Yes
Adj.-R^2	21.92	6.32

Table IA.6.18: Customer replacements and profit margins

The table reports the value-weighted characteristics of suppliers that recently replaced most of their customers, denoted by $\mathbb{I}_{Replacement} = 1$, and suppliers that did not, denoted by $\mathbb{I}_{Replacement} = 0$. For each firm i and each quarter t between June 2003 and December 2020 (i.e., for each quarter for which the FactSet data are available), we define the variable $Replace_{i,t}$ as the minimum between the number of links with old customers that broke between time $t-1$ and time t, and the number of links with new customers that formed between time $t-1$ and t. We then set $\mathbb{I}_{Replacement}$ equal to one if at least 50% of the links between firm i and its customers at time $t-1$ were replaced by time t. We then compute the average profitability, operating costs, and idiosyncratic (firm-level) productivity across all firms in quarter t for which $\mathbb{I}_{Replacement} = 0$ and $\mathbb{I}_{Replacement} = 1$. We measure profitability using the quarterly values of dividends per share, profit margin, and ROA, we measure operating costs using the quarterly measure of Novy-Marx (2011), and we measure firm-level productivity following Imrohoroglu and Tuzel (2014). The column denoted by Difference reports the difference between the average characteristics for which $\mathbb{I}_{NewCustomers} = 0$ and for which $\mathbb{I}_{NewCustomers} = 1$, and the column denoted by t(Diff) is the Newey and West (1987) t-statistic associated with this difference.

Characteristic	$\mathbb{I}_{NewCustomers} = 0$	$\mathbb{I}_{NewCustomers} = 1$	Difference	t(Diff.)
Div. per share	0.25	0.16	0.09	(8.26)
Profit margin	0.03	-0.14	0.17	(2.89)
ROA (%)	1.60	0.81	0.79	(6.75)
Operating costs	-0.02	0.01	-0.03	(-2.68)
TFP	0.14	0.06	0.09	(10.22)

Table IA.6.19: R/S spread within industry portfolios

The table shows the results of a conditional double sort procedure. First, firms are sorted into nine groups based on their industry affiliation. Here, we use the Fama-French 10 industry classification to assign firms to industries, and drop firms assigned to the "Other" industry. Next, within each industry we sort firms into three portfolios based on R/S. Firms are sorted into portfolios at the end of each June following the portfolio formation procedure described in Section 1.2.1. The table then reports the mean return associated with each R/S-sorted portfolio, the low-minus-high R/S spread in each industry, and the Newey and West (1987) robust t-statistic associated with each R/S spread. In the final row of the table, the "Joint test" reports the p-value associated with the null hypotheses that the R/S spread is jointly equal to zero across the nine industries. Portfolio returns span July 1978 to December 2020.

Industry	Low R/S	Medium	High R/S	Spread	(L-H)
Energy	1.44	0.93	0.09	1.35	(3.32)
High Tech	1.66	1.20	0.37	1.29	(4.84)
Telecommunication	1.52	0.97	0.40	1.12	(2.54)
Health	1.73	1.20	0.81	0.92	(2.69)
Nondurable	1.46	1.13	1.08	0.38	(1.54)
Utilities	1.05	1.00	0.78	0.27	(0.74)
Shops	1.18	1.22	1.04	0.14	(0.62)
Manufacturing	0.91	1.08	0.83	0.08	(0.36)
Durable	0.90	1.06	1.03	-0.13	(-0.36)
				Joint test	($p < 0.01$)

Table IA.6.20: Fama-MacBeth regressions

The table reports the results of Fama-MacBeth regression that project future annual firm-level excess returns on each firm's current R/S ratio while controlling for various firm-level characteristics that are known to predict returns. Here, each variable is standardized by its unconditional standard deviation. The table reports the slope coefficient associated with each predictor, as well as the Newey and West (1987) robust t-statistic associated with each point estimate. The sample period is from July 1978 to December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R/S	-1.66	-1.72	-1.37	-1.41	-1.31	-1.27	-1.66	-1.62	-1.20
	(-2.46)	(-2.46)	(-2.22)	(-2.21)	(-1.99)	(-2.15)	(-2.55)	(-2.48)	(-2.16)
ln(ME)		-2.92							
		(-2.08)							
B/M			2.74						
			(2.91)						
MOM				-0.43					2.50
				(-0.43)					(2.82)
ROA					0.80				-0.14
					(0.83)				(-0.16)
I/K						-2.08			
						(-2.97)			
Cash/AT							0.81		1.66
							(0.80)		(1.74)
Leverage								-0.33	0.03
								(-0.46)	(0.05)
R^2	0.60	1.55	1.67	1.14	1.62	1.33	1.57	1.00	2.98

Table IA.6.21: Number of customers and stock returns
The table reports the average monthly returns of portfolios sorted on average number of customers per supplier based on FactSet relationship data ($NCust$), and the spread between the returns of the low and high ($NCust$) portfolios. The cross-section of firms is sorted into three portfolios based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the number of customers at the end of the previous month. Panel A reports the returns of portfolios constructed using $NCust$, whereas Panel B reports the returns of portfolios constructed using the industry-adjusted value of $NCust$, denoted by $NCust^{IA}$. This industry adjustment is implemented by (i) assigning each firm to its Fama-French 30 industry group, and (ii) subtracting each industry's cross-sectional median number of customers from each firm's number of customers. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics. All portfolios are formed at the end of each June from 1978 to 2020 and are rebalanced annually. Consequently, portfolio returns span July 1978 to December 2020.

	Panel A: $NCust$		Panel B: $NCust^{IA}$	
Portfolio	Mean	SD	Mean	SD
Low $NCust$	0.980	4.345	1.167	5.596
Medium	1.010	3.951	1.036	4.023
High $NCust$	1.111	4.357	1.057	4.181
Spread	-0.131	2.320	0.110	3.081
(L-H)	(-0.81)		(0.49)	

Table IA.6.22: Sort on accounts payable to cost of goods sold
The table reports the average monthly returns of portfolios sorted on the ratio of account payables to cost of goods solds ($AP/COGS$), and the spread between the returns of the low and high $AP/COGS$ portfolios. The low (high) $AP/COGS$ portfolio includes all firms with $AP/COGS$ ratios below (above) the 10^{th} (90^{th}) percentiles of the cross-sectional distribution of $AP/COGS$ ratios from fiscal years ending in calendar years $t-1$. Panel A reports the returns of portfolios constructed using the $AP/COGS$ ratio, whereas Panel B reports the returns of portfolios constructed using the industry-adjusted AP/COGS ratio, denoted by $AP/COGS^{IA}$. This industry adjustment is implemented by (i) assigning each firm to its Fama-French 30 industry group, and (ii) subtracting each industry's cross-sectional median $AP/COGS$ ratio from each firm's $AP/COGS$ ratio. Both panels report value-weighted returns. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics. All portfolios are formed at the end of each June from 1978 to 2020 and are rebalanced annually. Consequently, portfolio returns span July 1978 to December 2020.

	Panel A: $AP/COGS$		Panel B: $AP/COGS^{IA}$	
Portfolio	Mean	SD	Mean	SD
Low $AP/COGS$	1.154	5.293	1.145	5.169
Medium	1.096	4.595	1.103	4.715
High $AP/COGS$	0.940	5.710	0.964	5.474
Spread	0.214	3.662	0.180	3.790
(L-H)	(1.16)		(1.09)	

Table IA.6.23: Controlling for upstreamness: double-sort analysis

The table reports the average monthly value-weighted portfolio returns obtained from a conditional double-sort related to the upstreamness of each firm in the production network. Here, the control variable is the upstreamness of each supplier, and the second-stage sorting variable is a firm's receivables-to-sales (R/S) ratio. The sort is conducted as follows. First, at the end of each June, we sort firms into three portfolios on the basis of upstreamness using the 33^{rd} and 66^{th} percentiles of the cross-sectional distribution of upstreamness in month $t-1$. Second, within each upstreamness-sorted portfolio, we further sort firms into three portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning for July in year t to the end of June in year $t+1$, when all portfolios are rebalanced. Parentheses report p-values associated with the magnitude of the R/S spread computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three duration-sorted portfolios is zero. Finally, the sample period is from July 1978 to December 2020.

	Low VP	Medium	High VP	
Low R/S	1.27	1.17	1.03	
Medium	1.23	1.07	1.07	
High R/S	0.87	0.59	0.52	
Spread	0.41	0.58	0.51	Joint test
(L-H)	($p = 0.03$)	($p = 0.01$)	($p = 0.01$)	($p = 0.01$)

Table IA.6.24: Controlling for centrality: double-sort analysis

The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first-stage sorting variable) is a firm's eigenvalue centrality, as in Ahern (2013), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of centrality using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution in calendar year $t-1$. Second, within each centrality-sorted portfolio, we further sort firms into three additional portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning of July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. The last two rows of each panel show the R/S spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three characteristic-sorted portfolios is zero.

	Low centrality	Medium	High centrality	
Low R/S	-0.14	1.47	3.40	
Medium	1.59	1.02	1.26	
High R/S	0.49	0.87	0.83	
Spread	-0.63	0.61	2.57	Joint test
(L-H)	($p = 0.77$)	($p = 0.06$)	($p = 0.04$)	($p = 0.07$)

Table IA.6.25: Predicting consumption growth using macro shocks

The table reports the results of following regression: $\frac{1}{k}\Delta c_{t\rightarrow t+h} = const + \beta_{R/S}\Delta\overline{R/S}_t + \beta_{MKT}MKTRF_t + error$, where k is the predictive horizon, Δc is log consumption growth, $\Delta\overline{R/S}_t$ is the innovation to the aggregate receivables to sales ratio, and $MKTRF$ is the market excess return. Note that the independent variables correspond to the two shocks that drive the SDF in equation (6). We measure consumption growth using the unfiltered NIPA consumption (as in Kroencke (2017)). We use four measures for consumption growth: the annual growth of non-durables and services consumption (Panel A), the annual growth rate of non-durables consumption only (Panel B), the fourth quarter to fourth quarter growth rate of non-durables and services consumption (Panel C), and the fourth quarter to fourth quarter growth rate of non-durables consumption only. The use of the fourth quarter to fourth quarter consumption growth rate follows Jagannathan and Wang (2007). Parentheses show Newey and West (1987) t-statistic. The sample period is annual from 1979 to 2018.

Horizon (years)	$\beta_{R/S}$	$t(\beta_{R/S})$	β_{MKTRF}	$t(\beta_{MKTRF})$	R^2
Panel A: Non-durable and services					
$h=1$	-0.25	(-1.99)	0.52	(3.86)	24.29
$h=2$	-0.35	(-2.55)	0.30	(2.31)	12.65
$h=3$	-0.17	(-1.47)	0.24	(2.10)	2.03
Panel B: Non-durable					
$h=1$	-0.38	(-3.29)	0.45	(3.75)	24.36
$h=2$	-0.38	(-2.71)	0.19	(1.59)	10.40
$h=3$	-0.23	(-1.66)	0.17	(1.32)	1.76
Panel C: Non-durable and services (Q4-Q4; Jagannathan and Wang, 2007)					
$h=1$	-0.37	(-2.87)	0.37	(2.51)	18.12
$h=2$	-0.27	(-2.00)	0.10	(0.72)	2.17
$h=3$	-0.10	(-0.91)	0.16	(1.32)	2.48
Panel D: Non-durable (Q4-Q4; Jagannathan and Wang, 2007)					
$h=1$	-0.50	(-3.68)	0.27	(2.45)	23.57
$h=2$	-0.33	(-1.94)	0.00	(0.02)	5.59
$h=3$	-0.20	(-1.26)	0.12	(0.96)	-0.59

Table IA.6.26: GMM analysis with search-cost proxies

The table reports the GMM pricing errors and estimates of the parameters underlying the stochastic discount factor (SDF) represented by equation (6) and the Euler equation represented by equation (7). Panel A reports the model-implied pricing errors associated with the GMM procedure, while Panel B reports the covariance of each portfolio with the different macroeconomic shocks included in the two-factor SDF, which always includes the excess returns of the market portfolio (denoted by MKTRF). The additional macroeconomic shocks included in this SDF include (i) the death-minus-birth rate (denoted by DMB), and (ii) the relative competition (denoted by HHI) measures described in Section 2.1. Here, the test assets are the 10 R/S-sorted portfolios, which are constructed following the procedure outlined in Section 1.2. Panel C reports the market price of risk associated with MKTRF and each macro variable when the test assets are the 10 R/S-sorted portfolios. The data underlying these analysis is annual, and spans 1978 (1992) to 2020 for the column labelled DMB (HHI). Finally, parentheses reported Newey and West (1987) t-statistics.

	DMB	HHI
Panel A: Model-implied alphas		
Low R/S	1.49	0.44
Medium R/S	1.53	1.39
High R/S	0.36	0.59
Spread	1.13	-0.15
(L-H)	(0.91)	(-0.10)
Panel B: Covariance with macroeconomic variable		
Low R/S	-0.34	-0.34
Medium R/S	-0.27	-0.22
High R/S	-0.16	0.02
Spread	-0.18	-0.36
(L-H)	(-1.91)	(-2.61)
Panel C: Market prices of risk with R/S portfolios		
b_{MKTRF}	0.27	1.04
	(0.44)	(1.29)
b_{MACRO}	-29.46	-27.46
	(-3.60)	(-4.71)
MAE	1.74	0.69

Table IA.6.27: GMM analysis with alternative innovations to aggregate R/S ratio

The table reports the GMM pricing errors and estimates of the parameters underlying the stochastic discount factor (SDF) represented by equation (6) and the Euler equation represented by equation (7). Panel A reports the model-implied pricing errors associated with the GMM procedure, while Panel B reports the covariance of each portfolio with the $MACRO_t$ shock included in the two-factor SDF, which always includes the excess returns of the market portfolio (denoted by MKTRF). The additional macroeconomic shocks included in this SDF are innovations to aggregate R/S ratio, constructed as the aggregate ratio of changes in receivables to lagged sales. Here, the test assets are the 10 R/S-sorted portfolios, which are constructed following the procedure outlined in Section 1.2. Panel C reports the market price of risk associated with MKTRF and the macro variable (divided by 100) when the test assets are the 10 R/S-sorted portfolios. The data underlying these analysis is annual, and spans 1978 to 2020. Finally, parentheses reported Newey and West (1987) t-statistics.

	R(t)-R(t-1)/S(t)
Panel A: Model-implied alphas	
Low R/S	3.05
Medium R/S	2.30
High R/S	1.09
Spread	1.96
(L-H)	(1.17)
Panel B: Covariance with macroeconomic variable	
Low R/S	-0.29
Medium R/S	-0.25
High R/S	-0.09
Spread	-0.20
(L-H)	(-1.90)
Panel C: Market prices of risk with R/S portfolios	
b_{MKTRF}	0.30
	(0.71)
b_{MACRO}	-33.52
	(-3.30)
MAE	2.77

Table IA.6.28: Model-implied market price of aggregate trade credit
This table presents the market price of risk for the macro-fundamental shocks that explains the counterparty premium using model simulated data. Specifically, we posit that the SDF take the following form:

$$M_{t,t+1} = 1 - \boldsymbol{b}'\boldsymbol{F}_t - b_{\overline{R/S}}\Delta\overline{R/S}_t,$$

where $\boldsymbol{F_t} = [MKTRF, SMB, HML]'$ (3 factors) or $\boldsymbol{F_t} = [MKTRF, SMB, HML, CMA, RMW]'$ (5 factors); $MKTRF$ is the excess market return, SMB is the size premium, HML is the value premium, CMA is the return spread between low and high investment firms, RMW is the return spread between high and low profit firms, and $\Delta\overline{R/S}_t$ represents innovations to the aggregate R/S ratio, measured by its log first-difference. We estimate $\boldsymbol{b}$ and $b_{\overline{R/S}}$ using GMM estimation of the Euler equation $E[M_{t,t+1}R_{i,t+1}] = 1$, where $R_{i,t+1}$ are the returns of the testing assets. We consider three cross-sections: (i) 10 portfolios sorted on size, 10 portfolios sorted on book-to-market, and 10 portfolios sorted on R/S; (ii) the same panel from point (i), less the portfolios sorted on R/S; (iii) all individual stocks in the cross-section of the simulated model. Parentheses represent t-statistics.

	Panel A: 10 ME, B/M, and R/S		Panel B: 10 ME and B/M		Panel C: All stocks	
	5 factor	3 factor	5 factor	3 factor	5 factor	3 factor
$b_{\overline{R/S}}$	-8.877	-8.851	-12.456	-12.078	-1.026	-1.145
	(-14.70)	(-15.36)	(-12.75)	(-12.96)	(-7.49)	(-8.38)

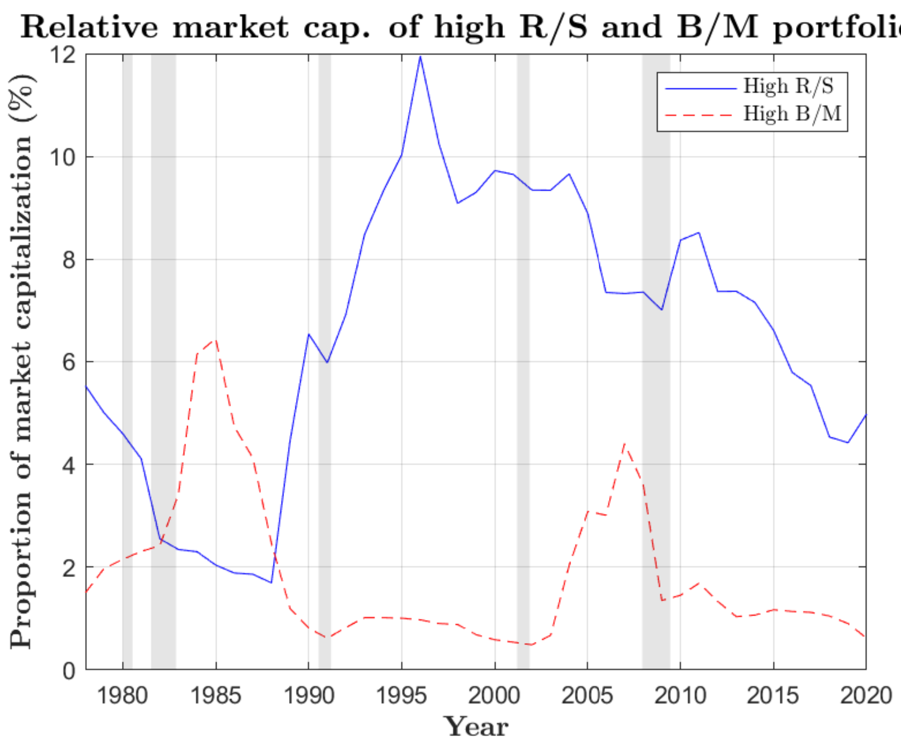

Figure IA.6.1: The table shows the annual time-series of the proportions of market capitalization represented by stocks in the high R/S and the high B/M portfolios. Here, a firm is classified as having high R/S or B/M ratio if its R/S or B/M ratio is above the 90^{th} percentile of the cross-sectional distribution of R/S or B/M ratios at the end of June of each year from 1978 to 2020.

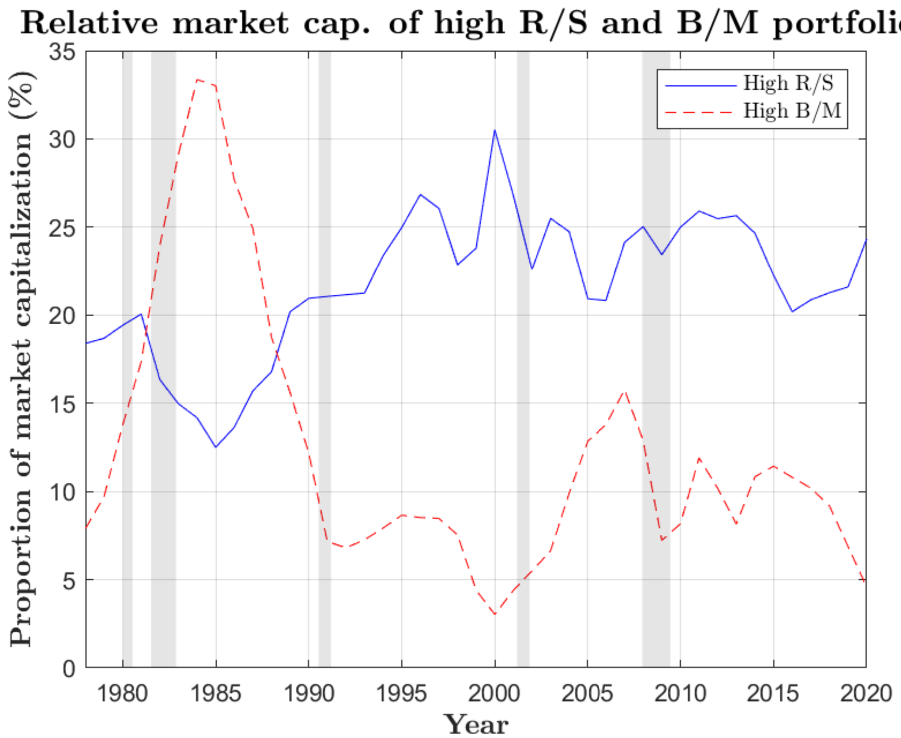

Figure IA.6.2: The table shows the annual time-series of the proportions of market capitalization represented by stocks in the high R/S and high B/M portfolios. Here, a firm is classified as having high R/S or B/M ratio if its R/S or B/M ratio is above the 70^{th} percentile of the cross-sectional distribution of R/S or B/M ratios at the end of June of each year from 1978 to 2020.

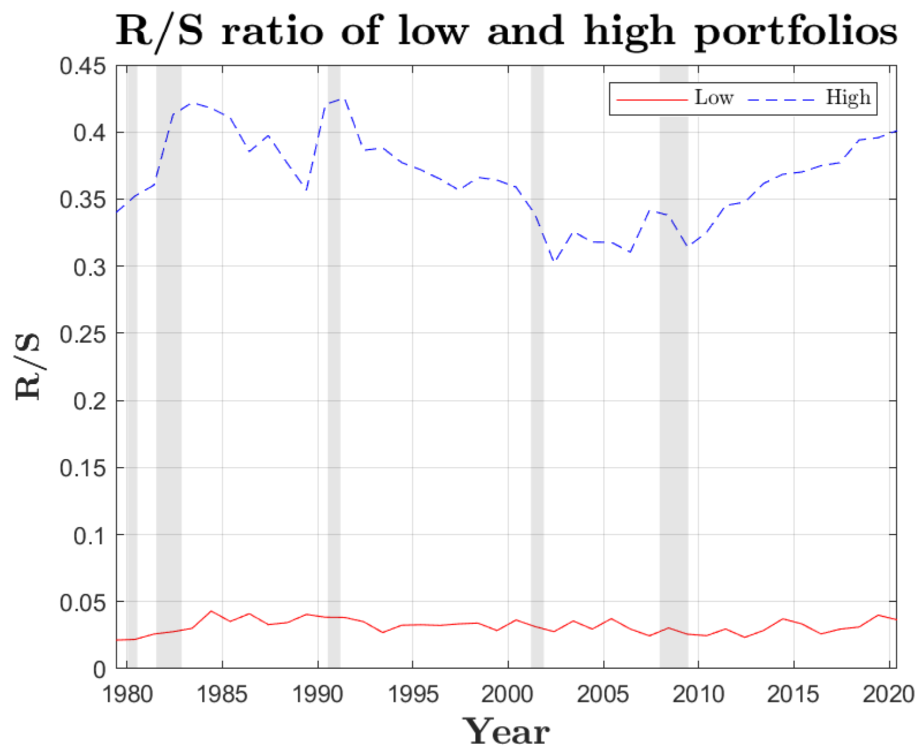

Figure IA.6.3: The figure displays the annual time-series of the average R/S ratio of both the low R/S portfolio (solid red line) and the high R/S portfolio (dashed red line) over our sample period of 1978 to 2020. Here, portfolios are formed by following the portfolio formation procedure outlined in Section 1.2.1.

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