Trade Counterparty Risk: Implications for Network Dynamics and Risk[⋆]

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Abstract

Firms with higher receivables-to-sales ratios (R/S) extend more trade credit, and thus have greater exposure to risks that impact their trade counterparties. Surprisingly however, high R/S firms command risk premia that are 6% per annum *lower* than those of low R/S firms. This novel R/S spread is not explained by common asset-pricing factors or characteristics, and a novel factor based on the spread is priced in the cross-section of returns. We use production network data to show that low R/S firms have shorter-lived (lower duration) links with their customers, and that low link duration firms command higher returns. We embed trade credit into the production-based asset-pricing framework to jointly explain these facts. In the model, receivables act as an insurance policy that suppliers may offer certain customers to hedge their liquidity risks. High R/S firms are endogenously matched with better counterparties, and the hedge they provide makes the links with their customers last longer. Consequently, high R/S firms are less exposed to costly frictions involved in the search for a new counterparty, and are therefore safer. Overall, our empirical and theoretical results show that R/S contains important information for forecasting the duration of supplier-customer links, which in turn impacts firms' riskiness and valuations.

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[⋆]All errors are our own.

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1 Introduction

Trade credit is a large component on the average firm's balance sheet. When goods are delivered to customers, supplier firms typically demand immediate cash payments for only a fraction of the sales, with the rest logged as accounts receivable. Consequently, firms that have higher levels of accounts receivable to sales (henceforth R/S) are more exposed to adverse shocks that deteriorate their customers' financial conditions. Indeed, Days Receivables, a widely used measure in financial accounting that is proportional to R/S, is used to evaluate firms' operating and counterparty risks. [1] Since defaults on trade credit tend to occur more often during economic downturns, firms with high accounts receivable, ceteris paribus, should be riskier and earn higher expected returns.

In this paper we show that contrary to this belief, high R/S firms are actually safer. Empirically, we show that high R/S firms earn a significantly lower risk premium. The spread between the average returns of low and high R/S firms is close to 0.60% per month, or above 6% per annum. This counterparty premium is not only puzzling from the traditional accounting view of R/S, but is also puzzling from the standpoint of traditional asset-pricing factors. The spread yields significant and positive alphas when projected on common asset-pricing factors. Additionally, we use a GMM procedure to provide evidence that a novel counterparty risk factor is priced in the cross-section of stock returns, with a negative factor risk premium.

The counterparty premium is also puzzling due to the fact that it cannot be explained using common characteristics from Compustat that are known to command risk premia. There are no statistical differences between low and high R/S firms in terms of key characteristics such as size, book-to-market, momentum, or investment rates. While low R/S firms have low accruals, low idiosyncratic volatility, and high profitability, conditional portfolio double-sorts show that the counterparty premium remains positive and significant when controlling for each of these characteristics. Furthermore, while the average counterparty premium remains significant across accruals-sorted portfolios, the converse does not hold. The accruals effect is, on average, insignificant across R/S-sorted portfolios. This suggests that the economic determinants of the R/S spread could also explain the accruals premium.

To explore the economic forces behind the counterparty premium, we examine network data on firm-level supplier-customer relationships. While common network characteristics

[1] In this paper we use the term "counterparty risk" to mean the risk associated with dealing with a trade partner, including all risks incurred by a firm's customer that the supplier firm is exposed to via trade (extending trade credit to the customer).

such as centrality do not help explain the premium, we find that, on average, low R/S firms have shorter-lived (lower duration) links with their customers. Furthermore, we document a significant duration premium: suppliers that maintain shorter duration links with their customers earn average returns that are 0.98% per month higher than those earned by suppliers that maintain longer-lived (higher duration) links with their customers. A double-sort analysis shows that this duration premium explains a majority of the R/S spread within the subsample for which supplier-customer relationship data is available. This result suggests that R/S ratios contain important information that is positively correlated with the expected length of supplier-customer relationships that is otherwise hard to observe. Indeed, "horse race" regressions show that R/S emerges as the best predictor for the persistence of supplier-customer links. Thus, our empirical results not only shed light on why low R/S firms are risky, but also demonstrate how the provision of trade credit can shape the dynamics of the production network's supplier-customer connections.

We build a quantitative model to explain the two prominent facts: (1) low R/S firms have higher returns, and (2) higher receivables-to-sales implies a lower probability of a supplier-customer link breaking. Our model builds on the theoretical microfoundation for trade credit proposed by Cunat (2006), but extends the framework by featuring production and matching frictions between suppliers and potential customers. In the model, each supplier firm is matched with a customer of heterogeneous quality. A higher quality customer increases the supplier's revenue. Better quality can capture either a positive spillover from the productivity of the customer to that of the supplier (i.e, more productive customers demand more inputs), or a higher markup that the supplier can charge the customer for selling a specialized product. While the link between the supplier and its customer is alive, the customer may experience a liquidity shock that exposes the supplier to the default risk by its counterparty. Default implies that the customer cannot repay its supplier the accounts receivable extended in the previous period. Additionally, if the customer defaults, the supplier has to search for a new customer. This search involving some frictions. Specifically, the supplier has to pay a search cost and draw a new customer from an i.i.d. distribution. Every period, the supplier chooses investments in physical capital and the amount of trade credit to offer its customer. More trade credit provides the customer with more insurance to hedge against its liquidity shocks, and therefore reduces the probability of the customer defaulting. This feature is largely consistent with empirical evidence (see, e.g., Garcia-Appendini and Montoriol-Garriga, 2013).

We specify the stochastic discount factor with two aggregate shocks that are priced. The first factor is the standard aggregate productivity which impacts firms' output and has a positive price of risk. The second factor, which we name the counterparty factor, captures the cost of searching for a new customer. We assign this factor a negative market price of risk to be consistent with the data. Although not explicitly modeled, an increase in the search cost may capture an aggregate economic state with fewer candidate customer firms looking for suppliers (e.g., the pool of new entrants shrinks, resulting in a harder search), a state with higher competition among suppliers (e.g., lower bargaining power with new customers), or a state with increased regulation (e.g., more costly to contract with a potential customer).

High R/S are endogenously safer in the model for two primary reasons. First, these firms have a less negative exposure to the counterparty factor. Coupled with a negative price of risk for this factor, the risk premium is therefore lower for these firms. This happens because higher R/S firms provide more insurance to their customer against liquidity shocks, increasing the likelihood that the supplier-customer link will survive longer. As a result, high R/S firms are less likely to search for a new customer next period, and have lower exposure (in absolute value) to the systematic shock that affects the rematching cost. Put differently, high R/S act as a hedging device against the frictions involved in the search for new customers. Second, higher R/S suggests that, all else equal, the firm is currently matched with a higher quality customer. This is because firms have a greater incentive to keep (hedge) better customers by extending more receivables. In the model, higher quality customers are safer for the firm. Higher quality implies higher sales, lower operating (leverage) risk, and thus, lower exposure to aggregate productivity. While both channels make high R/S firms safer, the first channel is more dominant. The model quantitatively matches the counterparty risk premium to the data, as well as key investment and R/S-related moments.

The rest of this paper is organized as follows. We provide an overview of related literature in Section 2. Section 3 empirically examines the relation between trade counterparty risk and expected returns, and shows that a counterparty risk factor is priced in the cross-section of stock returns. Section 4 examines the economic origins of the counterparty risk premium using network data on supplier-customer relationships. Sections 5 and 6 quantitatively demonstrates the endogenous relation between counterparty risk, expected stock returns, and links' duration through the lens of a production-based asset pricing model. Finally, Section 7 provides concluding remarks.

2 Related literature

This study connects the literature on the role of trade credit in corporate finance to the literature on production-based asset pricing. Specifically, to the best of our knowledge, this is the first paper to quantitatively document how a firm's decision to offer trade credit impacts its expected returns.

On the corporate finance front, a number of studies examine when, and why, suppliers offer trade credit to their customers. Garcia-Appendini and Montoriol-Garriga (2013) shows that during the 2007-2008 financial crisis, firms with high precrisis liquidity levels increased trade credit extended to corporations that are financially constrained and subsequently experienced better performance. This is consistent with both the view that trade credit acts as liquidity insurance (Cunat, 2006; Wilner, 2000) particularly when bank credit is scarce, and theories that trade credit is a substitute for bank credit (Biais and Gollier, 1997; Burkart and Ellingsen, 2004). Burkart and Ellingsen (2004) assume input is less profitable to divert than cash, meaning suppliers have a natural advantage in lending compared to banks. Similarly, Frank and Maksimovic (1998) argue that suppliers have a comparative advantage over banks in liquidating certain types of inventories. Ferris (1981) suggests that the use of trade credit reduces a firm's need to hold precautionary cash because trade creditors can reduce transaction costs when there is uncertainty about delivery times and production needs.

When there is a contraction in aggregate bank credit supply, banks reduce lending to risky firms. Nilsen (2002) shows in such tight conditions, large firms who still have access to market financing such as commercial papers, extend more trade credit to small firms who are cut off from bank credit. This is consistent with the view of Meltzer (1960) regarding the trade credit channel of monetary policy.

Our paper is also consistent with McMillan and Woodruff (1999), who show that firms are more likely to offer trade credit to customers with whom they have exclusive buyer-seller relationships. Also consistent is the evidence from Petersen and Rajan (1997), who show that suppliers of trade credit continue to provide credit even to firms with negative profits, but only if their customers' sales are increasing. Finally, Ng, Smith, and Smith (1999) report that firms are willing to loosen conditions on trade credit, especially for long-term customers.

On the asset-pricing front, our paper is related to studies that connect production-related firm characteristics to expected returns. Specifically, this is the first paper to quantitatively examine the implications of suppliers' trade credit policies for risk premia. Traditional studies in this literature rely on ex-post cross-sectional differences in capital adjustment costs (e.g., Zhang (2005), Belo and Lin (2012), and Jones and Tuzel (2013)) or labor market frictions (e.g., Belo, Lin, and Bazdresch (2014)) to explain differences in risk premia, through heterogeneous exposures to aggregate productivity. Our study proposes an alternative and novel mechanism: time varying and heterogeneous exposures to systematic frictions involved in the search for potential customers. We show how these frictions influence a supplier's decision to offer trade credit and endogenously determines the firm's expected stock returns.

3 The counterparty risk premium

3.1 Stock return and accounting data

Monthly stock return data are taken from the Center for Research in Security Prices (CRSP). Firm-level accounting data, such as trade receivables and sales, are taken from the CRSP/Compustat Merged Fundamentals Annual file. We obtain asset pricing factors related to the Fama and French (1993, 2015) three- and five-factor models, and the Carhart (1997) four-factor model, from the data library of Kenneth French. Data related to the Hou, Xue, and Zhang (2015) q-factor model are provided by Lu Zhang.[2] The definitions of the accounting ratios used in this paper are provided in Section OA.1 of the Online Appendix.

Our sample includes the common equity of all firms in the CRSP/Compustat universe listed on the NYSE/AMEX/NASDAQ exchanges, excluding financial firms (SIC codes 6000 to 6999) and public utilities (SIC codes 4900 to 4999). The time span of our analysis ranges from 1978 to 2016 because data on trade receivable is sparse prior to 1978. As a robustness check we verify that our results also persist in the most recent half of our sample period.[3]

3.2 Counterparty risk and expected stock returns

3.2.1 Measuring trade counterparty risk

We are primarily interested in the relation between the intensity of a firm's trade credit provision and its risk premium. We measure the trade counterparty of firm i at time t by scaling the firm's trade receivables by its average sales:

$$R/S_{i,t} = \frac{\text{Trade receivables}_{i,t}}{0.5 \times (\text{Sales}_{i,t} + \text{Sales}_{i,t-1})}. \tag{1}$$

Here, receivables and sales are both drawn from Compustat Annual.[4] This ratio, also known as Days Receivables when multiplied by 365, is often used to assess the effectiveness of a company's credit provision policies, and its ability to collect cash from sales made on credit.

Conventional wisdom in financial statement analysis suggests that high values of R/S indicate firms with low operating efficiency, as a result of higher exposure to default risk by

[2]We thank Kenneth French and Lu Zhang for making this data available.

[3]The results of this robustness check are reported in Table OA.2.1 of the Online Appendix.

[4]In Table OA.2.2 of the Online Appendix we also construct R/S using Compustat Quarterly data, and show that our key results hold when we use quarterly data. However, given that trade receivables data in Compustat Quarterly is very sparsely populated prior to the early 2000s, we use Compustat Annual data as in our benchmark analysis since this annual data lets us to begin our tests in the early 1970s.

customers, or as the result of lax receivables collection policies. Consequently, the traditional view of this ratio predicts that firms with high R/S are risky, and should earn high average returns. However, the relation between R/S and future stock returns is more nuanced than this conventional wisdom suggests.

Contrary to the common interpretation of the R/S ratio, low R/S does not necessarily reflect a firm with high operating efficiency or low counterparty risk. For example, suppliers may extend more trade credit to retain higher quality, and more productive, customers. This possibility, which we explore in more detail below, suggests that low R/S firms are risky because they are endogenously associated with less productive customers. Additionally, a relatively distressed firm may avoid selling on credit to either (1) avoid the possibility of inuring production costs upfront but losing future cash flows due to a customer default, or (2) satisfy precautionary motives for cash, such as avoiding costly external financing. In each of these situations a low R/S ratio reflects the underlying risk of a firm, and suggests that these low R/S firms should earn higher, rather than lower, average returns.

Given the theoretical relation between R/S and future stock returns is ex-ante ambiguous, we examine this relation empirically by sorting firms into portfolios based on R/S. Section 3.2.2 describes our portfolio formation procedure, while Section 3.2.3 presents the results.

3.2.2 Portfolio formation

To empirically examine the relation between trade counterparty risk and stock returns, we form portfolios by sorting the cross-section of firms on the basis of each firm's R/S ratio. Specifically, at the end of each June from 1978 to 2015, we sort firms into portfolios based on the value of R/S in the fiscal year ending in calendar year $t-1$. This lag between the release of accounting data and the June sort dates is conservative, but ensures that this strategy is tradable. This is because all data used to form portfolios are publicly available as of the portfolio sorting dates. Each portfolio is then held from July of year t to the end of June of year $t+1$, at which time all portfolios are rebalanced. This annual rebalancing allows us to capture conditional variation in the intensity of firm-level trade credit usage.

We form three portfolios on each June sort date. The low (high) R/S portfolio includes all firms whose R/S ratio is at or below (above) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of R/S ratios recorded in the fiscal year ending in calendar year $t-1$. The medium R/S portfolio includes the remaining firms whose receivables-to-sales ratios fall between these two breakpoints. We focus on these relatively extreme breakpoints to highlight the relation between R/S and expected stock returns. However, results reported in Section OA.2 of the Online Appendix show that our conclusions are robust to alternative choices of portfolio breakpoints.

Firm-level R/S ratios are not static since firms can alter the amount of trade credit they extend to their customers over time. Table OA.2.4 of the Online Appendix reports the annual transition probabilities between the R/S portfolios over the sample period. The table shows that 85% of firms with low R/S maintain a low R/S ratios between successive years, but only about 50% of firms with high values of R/S continue to offer a relatively large amount of trade credit between years. The persistence of R/S not only demonstrates how trade counterparty risk can affect the long-horizon risk premium of a firm, but also highlights the importance of the annual portfolio rebalancing procedure described above.

3.2.3 Return spread

Table 1 reports the monthly value- and equal-weighted returns of portfolios sorted on R/S using the procedure described above. The main empirical finding we document is an economically and statistically significant spread between the returns of low and high R/S firms. The portfolio of firms that extend a low amount of trade credit to their customers earns a value-weighted average return of 1.182% per month. In contrast, the portfolio of firms that extend relatively high amounts of trade credit to their customers earns a value-weighted return of 0.615% per month. Consequently, the value-weighted (equal-weighted) spread between the returns of the low and high R/S portfolios is 0.567% (0.683%) per month, and is statistically significant at the 5% (1%) level. The results also show that the value-weighted portfolio returns are monotonically decreasing in the average value of R/S. Furthermore, the annualized Sharpe ratios of the value- and equal-weighted R/S spreads are 0.44 and 0.68, respectively. These Sharpe ratios exceed the annualized Sharpe ratio of 0.36 earned by investing in the value premium over the same period.

Table 1 shows that the relation between R/S and stock returns runs contrary to what the conventional wisdom in financial statement analysis suggests. Although high R/S firms are typically perceived to have low operating efficiency and high counterparty risk, the average returns of these high R/S firms are significantly lower than those of low R/S firms. This decreasing relation between R/S and stock returns suggests that high R/S firms are, in fact, safer than low R/S firms. We refer to the approximately 6% per annum difference between the average returns of the low and high R/S firms as the *counterparty premium*.

Although the sign of the counterparty premium is puzzling from the traditional point of view in financial statement analysis, it may be subsumed by traditional asset pricing factors. In Section 3.3 we consider both whether common empirical asset-pricing model can explain the counterparty premium, and whether the counterparty premium is priced in the cross-section of stock returns. Similarly, in Section 3.4 we examine the characteristics of the R/S portfolios. This allows us to investigate both (1) what potentially makes low R/S firms risky, and (2) if the R/S spread is distinct from spreads related to characteristics that are known to command risk premia, such as profitability and accruals.

3.3 Systematic counterparty risk factor

In this section we empirically examine whether the counterparty premium is explained by a number of common unconditional asset-pricing models, such as the CAPM and Fama and French (1993) three-factor model. Our purpose is to understand whether the R/S spread contains any time-series variation that is unexplained by the workhorse factor models typically used to summarize the cross-section of equity returns. We also consider whether the counterparty premium is priced in the cross-section of stock returns.

We begin by projecting the monthly returns of the value-weighted R/S spread on the factors underlying five asset-pricing models: the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou et al. (2015) q-factor model. The results are presented in Table 2.[5]

The table shows that the monthly alphas obtained from these projections are always greater than 0.49% per month in magnitude, and exceed 0.75% per month in three out of the five cases considered. In addition, each of the five value-weighted alphas related to the counterparty premium is statistically significant at close to the 1% level, or better. The smallest t-statistic associated with the abnormal returns of the R/S spread is 2.55, and is obtained when the R/S spread is projected on the q factors of Hou et al. (2015). Collectively, these results demonstrate that the counterparty premium contains some time-series variation that is orthogonal to the variation in factor-mimicking portfolios based on characteristics such as size, book-to-market ratios, investment intensity, and profitability.

The fact that time-series variation in the counterparty premium is somewhat unrelated to numerous well-established asset-pricing factors suggests that trade counterparty risk may be an economically important and distinct determinant of stock returns. We examine this possibility by evaluating whether a counterparty risk factor is priced in the cross-section of stock returns. We undertake this analysis by assuming that the stochastic discount factor that prices all assets in the economy is specified as follows:

$$M_t = 1 - \boldsymbol{b}'\boldsymbol{f}_t + b_{CPR} CPR_t. \tag{2}$$

[5]Table OA.2.5 in the Online Appendix reports the results obtained by repeating the same analysis with the equal-weighted R/S spread in place of the value-weighted spread. The results obtained using the equal-weighted R/S spread are largely similar to those reported in Table 2 for the value-weighted spread.

Here, b_{CPR} is the parameter of interest that measures the market price of risk of a systematic counterparty risk factor denoted by CPR_t. We measure the counterparty risk factor via the spread between the value-weighted returns of the portfolio that buys high R/S firms and sells low R/S firms.[6] $\boldsymbol{b}$ is an $k \times 1$ column vector of additional risk factor loadings, and $\boldsymbol{f}$ is a $k \times 1$ column vector that contains either the excess market return only, or the Fama and French (1993) three factors. Finally, all factors underlying equation (2) are demeaned.

We estimate the risk factor loadings in equation (2) by generalized method of moments (GMM) using the following set of moment conditions:

$$\mathbb{E}_t \left[M_t r^e_{i,t} \right] = 0, \tag{3}$$

where $r^e_{i,t}$ denotes the excess return of test asset i at time t. We employ three sets of test assets to estimate the factor loadings. First, we estimate the the risk factor loadings using 25 value-weighted portfolios double sorted on size and book-to-market. Second, following the suggestion of Lewellen, Nagel, and Shanken (2010), we also estimate the factor loadings using a set of 42 portfolios that augments the first set of test assets with the Fama-French 17 value-weighted industry portfolios. This allows us to break the strong factor structure inherent in the returns of the 25 portfolios sorted on size and book-to-market. Third, we also estimate the factor loadings using a comprehensive set of 62 portfolios that augments the second set of test assets with 10 value-weighted portfolios sorted on each of investment and momentum. This large set of 62 portfolios not only allows us to measure the loading on the counterparty risk factor more precisely, but also allows us to examine whether a priced counterparty risk factor is a robust feature of the data.

Table 3 reports the results of the analysis described above. The table displays the factor loading associated with each risk factor across the three sets of test assets, as well as the mean absolute pricing error (MAE) from each GMM estimation of equation (3). In Panel A, we restrict the vector of additional risk factors in equation (2) to only include excess market returns. In Panel B, we allow this vector to also include the three Fama and French (1993) factors. Finally, using each set of test portfolios, we also consider the case in which b_{CPR} in equation (2) is set equal to zero. This allows us to examine the degree to which including the counterparty risk factor in equation (3) improves the fit of the model to the data (as measured by the decrease in MAE).

The results in Table 3 show that the factor loadings associated with the counterparty

[6]The spread captures any underlying systematic variable that makes low R/S firms riskier. To proxy for the factor, we use the spread of high minus low R/S, because $\beta_{CPR}^{R/S=HIGH} > \beta_{CPR}^{R/S=LOW}$ in the model of Section 5. Thus, shocks to the high minus low spread are *positively* correlated with shocks to the underlying counterparty factor. We discuss economic interpretations of this factor in Section 6.3.1.

risk factor are consistently negative, and are always statistically significant at the 5% level or better. This means that the counterparty risk factor is priced in the cross-section of returns, and carries a negative market price of risk. In particular, if all 62 test assets are included in the estimation procedure, and b_{CPR} is measured most precisely, then the market price of counterparty risk in Panel A (Panel B) is -5.961 (-5.294). Each of these risk factor loadings is also statistically significant at better than the 1% level. In addition to establishing that the counterparty risk factor carries a negative market price of risk, the table also shows that adding the factor to the CAPM or the Fama and French (1993) three-factor model can reduce the MAE of these models by up to 21%.

Taken together, the results in this section show that the counterparty premium is also puzzling from the lens of existing asset-pricing models. This is because the counterparty premium cannot be explained by five workhorse empirical asset-pricing models. In the next section we examine what potentially makes low R/S firms economically risky by examining the characteristics of the R/S-sorted portfolios. This allows us to understand whether R/S is correlated with other firm-level characteristics that are known to command risk premia, such as value, investment, and profitability.

3.4 Portfolio characteristics

This section documents the characteristics of the portfolios sorted on R/S, and examines whether the counterparty premium is related to other firm-level characteristics that are known to predict returns, such as value, investment, and profitability. The purpose of this analysis is to better understand why low R/S firms are risky.

We construct portfolio-level characteristics by value-weighting the characteristics of the firms assigned to each R/S portfolio on each June portfolio formation date. We then take the time-series average of these portfolio-level characteristics to document whether the R/S portfolios differ in regards to key characteristics. We ensure that any accounting data used to construct these characteristics are publicly available as of the relevant portfolio formation date. Table 4 reports the results of this analysis, as well as the differences between the average characteristics of the extreme R/S portfolios. Newey and West (1987) *t*-statistics associated with these differences are also reported in parentheses.

The table shows that the average value of R/S is, by construction, increasing monotonically from the low to the high R/S portfolio. However, the extreme R/S portfolios show no statistically significant differences in key characteristics, such as size, book-to-market ratios, investment rates (as measured by total asset growth), or momentum. This indicates that the counterparty premium extends beyond these common determinants of stock returns.

Moreover, high R/S firms are typically more highly levered despite having lower returns. The Hadlock and Pierce (2010) measure of financial constraints shows that these high R/S firms are not more financially constrained than low R/S firms. Thus, differences in financial constraints between firms are unlikely to explain the counterparty premium.[7]

The table does, however, raise the possibility that the counterparty premium may be related to the profitability, idiosyncratic return volatility (IVOL), or accruals effects. This is because low (high) R/S firms tend to be relatively profitable (unprofitable) firms with both low (high) IOVL and accruals. Each of these potentially confounding effects related to profitability, IVOL, and accruals is well-established in the context of the asset-pricing literature. For example, Fama and French (2006) demonstrate that more profitable firms typically earn higher returns. Similarly, Sloan (1996) and Ang, Hodrick, Xing, and Zhang (2006) document that firms with low accruals and IVOL, respectively, typically earn higher stock returns. The fact that low (high) R/S firms are also low (high) accruals firms is not surprising given that trade receivables are a large component of total accruals.

Given the differences in the aforementioned characteristics, Section 3.5 examines the degree to which the counterparty premium is independent of each of the profitability, IVOL, and accruals effects by conducting conditional portfolio double sort analyses. The results, reported in Table 5 and Table 6, show that the R/S spread always positive, and is typically economically sizable and statistically significant, after controlling for each characteristic. Thus, the counterparty premium cannot be explained by these key characteristics constructed using CRSP/Compustat data.

3.5 Distinction between counterparty risk and related spreads

In this section we conditionally sort the sample of firms into portfolios along two dimensions. The first dimension corresponds to either profitability, IVOL, or accruals, while the second dimension corresponds to R/S. This methodology allows us to examine the magnitude of the R/S spread while controlling for each of the profitability, IVOL, and accruals effects. We focus on profitability, IVOL, and accruals since these are the only three characteristics in Table 4 that are significantly different between the extreme R/S portfolios, and also command a risk premium that is aligned with R/S spread. Below, we describe the portfolio formation procedure that is used to undertake this analysis.

At the end of each June from 1978 to 2016 we first sort the cross-section of firms into

[7]Relatedly, Table OA.2.6 in the Online Appendix shows that financial distress cannot explain the counterparty premium either. That is, after controlling for either the Ohlson (1980) or Campbell, Hilscher, and Szilagyi (2008) measure of financial distress, we still document a quantitatively large and statistically significant counterparty premium.

three portfolios based on either profitability, IVOL, or accruals. We use the 10^{th} and 90^{th} percentiles of the firm-level cross-sectional distribution of each characteristic to assign firms into one of three portfolios. Next, *within* each of these three characteristic-sorted portfolios, we further sort firms into three additional portfolios on the basis of R/S. We also use the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of R/S to determine portfolio membership in this second step. This process produces nine portfolios that are 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. We ensure that all accounting data used to form portfolios in either step of the procedure are publicly available by using data from the fiscal year ending in calendar year $t - 1$ to form portfolios in year t.

Section 3.5.1 reports the results of this analysis when first controlling for either profitability or IVOL, while Section 3.5.2 reports the results when controlling for accruals.

3.5.1 Independence from profitability and idiosyncratic volatility

Fama and French (2006) demonstrate that firms with higher profitability typically earn higher future stock returns, while Ang et al. (2006) demonstrate that firms with lower IVOL typically earn higher stock returns. Since firms with low R/S not only earn high future returns, but also have high ROA and low IVOL, it is important for us to determine whether the counterparty premium is distinct from the profitability premium and the IVOL effect. The results of this analysis are presented in Table 5. The table reports the value-weighted returns from a conditional double-sort procedure in which the first dimension sorting variable in Panel A (Panel B) is ROA (IVOL), and the second stage sorting variable is R/S. The bottom two rows of each panel show the R/S spread, along with its associated p-value, within portfolios that control for each characteristic. Additionally, the rightmost column of each panel reports the p-value from a joint test on the null hypothesis that the counterparty risk premium across all three characteristic-sorted portfolios is zero.

The results in Panel A show that after controlling for profitability, the counterparty premium remains positive and significant within each ROA portfolio. The counterparty premium is not only economically sizable in all three cases, exceeding 1% per month among low profitability firms, 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 within each IVOL portfolio. The magnitude of R/S spread not only exceeds 1% per month within the portfolio of high IVOL firms, but is also statistically significant at the 1% level among medium IVOL firms. Although the R/S spread is statistically insignificant within the low IVOL portfolio, the null hypotheses that the counterparty premium is jointly zero across the three IVOL-sorted portfolios is still rejected at the 1% level.

Overall, the results in Table 5 indicate that neither the profitability premium nor the IVOL effect is driving the counterparty premium. Consequently, there appears to be meaningful variation in the cross-section of R/S ratios that cannot be attributed to these two determinants of expected stock returns.

3.5.2 The counterparty premium versus the accruals effect

Sloan (1996) shows that firms with lower accruals earn higher future returns. This pattern in stock returns is attributed to investors overestimating the persistence of accruals when forecasting future accounting earnings. Since the R/S spread is aligned with the aforementioned pattern in accruals (see Table 4), we empirically examine whether the counterparty premium survives controlling for accruals. Furthermore, we also explore the opposite relation and examine whether R/S can explain the accruals effect. This analysis is motivated by the definition of the total accruals of firm i and time t, which Sloan (1996) defines as:

$$\text{Accruals}_{i,t} = \frac{(\Delta\text{ACT}_{i,t} - \Delta\text{CHE}_{i,t}) - (\Delta\text{LCT}_{i,t} - \Delta\text{DLTT}_{i,t} - \Delta\text{TXP}_{i,t}) - \text{DP}_{i,t}}{0.5 \times (\text{AT}_{i,t} + \text{AT}_{i,t-1})}. \quad (4)$$

Here, variables are referred to by their mnemonics in the Compustat Annual dataset. Since trade receivables are a component of current and total assets (ACT and AT in the equation above, respectively), equation (4) raises the concern that the R/S spread is a manifestation of the accruals effect. However, this same close relation between receivables and accruals also raises the possibility that the determinants of the R/S spread can also (partially) explain the accruals puzzle. We empirically consider each of these possibilities below.

We begin by examining whether the R/S spread survives controlling for the accruals component of earning. We conduct this analysis using the dependent double sort procedure described in Section 3.5. In other words, we construct the R/S spread within three accruals-sorted portfolios. The results are reported in Panel A of Table 6 and show that the R/S spread earns over 0.50% per month among medium and high accruals firms. The R/S spreads within these two accruals-sorted portfolio are statistically significant at the 1% and 10% level, respectively. Furthermore, the joint test on the magnitude of the counterparty premium across the three accruals portfolios is statistically significant at the 5%. Collectively, this evidence suggests that the R/S spread is distinct from the accruals effect.

In Panel B of Table 6 we change the order of the sorts to examine whether the accruals effect survives controlling for R/S. The results show that the accruals effect is only statistically significant within the portfolio of medium R/S firms. The accruals spread generates a return of approximately 0.40% per month within this medium R/S portfolio. However, the joint test on the magnitude of the accruals effect across the three receivables-sorted portfolios is not rejected. This means that, after controlling for trade receivables, the average accruals effect is statistically indistinguishable from zero. Since conditioning portfolios on trade receivables drives out the accruals effect, while controlling for accruals does not subsume the R/S spread, the economic determinants of the counterparty premium may also shed light on the accruals puzzle of Sloan (1996).

Overall, the results in this section establish that the counterparty premium is a robust feature of the data. The counterparty premium cannot be explained by either common empirical asset-pricing models (recall Table 2) or firm-level characteristics computed using CRSP/Compustat data that are known to predict future returns (recall Table 4). Specifically, while the intensity of trade credit usage is correlated with firm-level profitability, IVOL, and accruals, the portfolio double sorts above show that none of these characteristics explain the R/S. In the next section we go beyond Compustat data and examine granular network data on supplier-customer relationships to shed light on the economic forces that drive the counterparty premium.

4 Trade credit in production networks

In this section we empirically examine the economic origins of the counterparty premium using granular supplier-customer relationship data. Our source of firm-level production-network data is the FactSet Revere relationships database, which is available beginning in April 2003. This data contains a comprehensive panel of supplier-customer links that allows us to document how trade credit usage is related to network characteristics, such as the number of customers per supplier and the average duration of supplier-customer links. The data also lets us examine how trade credit usage shapes the structure of production networks.

The FactSet data is ideal for our purpose because alternative data sources for supplier-customer relationships are either not as granular as FactSet (e.g., Compustat Segment data only reports a supplier's largest customers at the annual frequency), or do not specify with sufficiently high frequency when inter-firm relationships begin and end (e.g., Capital IQ and Bloomberg).[8] In contrast, FactSet uses information from a combination of accounting state-

[8] For example, the FactSet Revere database has over 20,000 supplier-customer relationships covering 4,000 customer firms in 2003. In contrast, the the Compustat Segment database has fewer than 2,500 supplier-customer relationships covering fewer than 1,000 customer firms in the same year.

ments, press releases, investor presentations, corporate announcements, and firms' websites to build a detailed picture of the relationships between firms that is updated daily. Importantly, by reporting both the start and end date of each supplier-customer link, the FactSet data allows us to empirically evaluate how suppliers' trade credit policies influence the duration of supplier-customer link and other features of the production network. Additional details on this FactSet relationship data, along with details on how we clean and link the data to CRSP/Compustat, are outlined by Gofman, Segal, and Wu (2018).

4.1 Network-related characteristics and counterparty risk

We begin our analysis of firm-level network data by considering whether high and low R/S firms differ in terms of key network-related characteristics, such as network centrality and the upstreamness of each firm in the production network. For example, Ahern (2013) shows that industries with higher network centrality earn higher returns, and Gofman et al. (2018) document that more upstream firms (those further away from final goods users) also earn higher returns. In addition, we also consider whether the average number of customers associated with each supplier and the average duration of each supplier-customer link going forward (measured in months) is related to the intensity of trade credit usage. Each of these network characteristics is described in Section OA.1 of the Online Appendix, and is only computed for suppliers that trade with more than one customer. The network-related characteristics of the R/S portfolios are reported in Table 7.

The table shows that network centrality cannot explain the counterparty premium, as the receivables-sorted portfolios are indistinguishable in terms of this characteristics. High R/S firms are typically more upstream producers than low R/S firms. This, nonetheless, cannot explain the spread as Gofman et al. (2018) show that more upstream firms earn higher returns. In contrast, Table 1 documents that high R/S firms earn lower, rather than higher, stock returns. The network-related characteristics in Table 7 do, however, suggest that the counterparty premium may be related to the number of customers associated with each supplier or the average life of supplier-customer links. High R/S firms are not only typically matched to significantly more customers than low R/S firms, but these high R/S firms also maintain their supplier-customer relationships for about one year longer than low R/S firms. To understand whether these two characteristic provide insights into the drivers of the counterparty premium, we consider each characteristic's relation to stock returns below.

4.2 The link duration premium

To investigate whether (1) the number of customers associated with each supplier, or (2) the average duration of supplier-customer links, may shed light on the economic determinants of the counterparty premium, we first conduct univariate portfolio sorts using each characteristic. This allows us to determine whether either of these two network-related characteristics commands a risk premium that is aligned with the R/S spread. We implement these portfolio sorts using the same portfolio formation procedure described in Section 3.2.2, with two exceptions. First, the sorts here begin in April 2003 instead of June 1978 since the FactSet data is only available from April 2003. Second, we rebalance the portfolios monthly instead of annually to alleviate losses in statistical power due to the shorter sample period.

The results of the univariate portfolio sorts are presented in Panel A of Table 8. On the one hand, Panel A shows that there is no return spread associated with the number of customers per supplier. On the other hand, Panel A shows that there is an economically large, statistically significant, and novel spread associated with the average duration of supplier-customer links. Specifically, suppliers that maintain shorter relationships with their customers earn average returns that are 0.98% per month greater those earned by suppliers that maintain longer relationships with their customers. This duration premium, which is aligned with the R/S spread, suggests that the economic origin of the counterparty premium is potentially related to the duration of supplier-customer links.

To illustrate how trade credit usage and the duration of supplier-customer links may interact, consider the role of trade credit in Cunat (2006). The study suggests that suppliers that extend more credit to their customers can protect their customers from liquidity shocks that threaten the survival of supplier-customer links. If, in addition, the search for new customers is costly, then these high R/S firms that offer more credit (insurance) to their customers are less likely to re-engage in costly searches for new counterparties. Ultimately, this would mean that high R/S firms that maintain longer duration links with their customers may be less risky than low R/S firms, resulting in the counterparty premium.

To examine whether the duration of supplier-customer links can explain the counterparty premium, Panel B of Table 8 reports the results of a conditional portfolio double sort analysis. The double-sort procedure is identical to that described in Section 3.5 except for the fact that the analysis begins at the end of June 2003. In the first stage of the procedure we control for suppliers' link durations, while the second stage of the procedure constructs the R/S spread *within* each duration-sorted portfolio. This allows us to directly test whether link duration can explain the counterparty premium.

The results in Panel B show that the counterparty premium is jointly equal to zero across the three duration-sorted portfolios. Among low duration suppliers, the R/S spread is close to 1% per month, but is only statistically significant at the 10% level. The R/S spread is qualitatively negative within the medium duration portfolio, and the spread is statistically indistinguishable from zero among high duration suppliers. Taken together, the evidence shows that the average duration of supplier-customer links drives out the counterparty premium. Consequently, understanding the interaction between the intensity of a supplier's trade credit provision and the average duration of its supplier-customer links is pivotal for explaining why high R/S firms are less risky than low R/S firms.

4.3 Predicting supplier-customer link duration with trade credit

This section implements a regression analysis to explore the interaction between supplier-level characteristics and the average life of supplier-customer links. Our purpose is to understand how a supplier's policies, including the provision of trade credit, shapes the dynamic network of inter-firm relationships. To this end, we estimate Fama-MacBeth regressions that use supplier-level characteristics to predict both (1) the expected duration of a supplier's links with its customers, and (2) the probability that supplier-customer links break.

The regressions are implemented as follows. First, at the end of June of each year t beginning in 2003, data from FactSet is used to identify each active supplier (denoted by s). Next, we estimate a cross-sectional regression that projects $D_{s,t}$, a forward-looking supplier-specific measure of link duration, on a set of supplier level characteristics. The two supplier-specific measures of link duration we use are (1) the average life of a supplier's links going forward (in months), and (2) an indicator variable that identifies the event in which a supplier's links with its customers break. Here, this indicator variable takes on a value of one if half of the supplier-customer links that are alive in year t do not survive until year $t+3$. This definition of the indicator variable is motivated by the fact that the average duration of supplier-customer links in the FactSet data is about three to four years (recall Table 7). The supplier-level characteristics used as predictors are the R/S ratio, the natural logarithm of the supplier's market value, investment rate, and profitability. Thus, the cross-sectional regressions specification is:

$$D_{s,t} = \beta_{0,t} + \beta_{1,t} R/S_{s,t} + \beta_{2,t} \ln(\mathrm{ME})_{s,t} + \beta_{3,t} I/K_{s,t} + \beta_{4,t} ROA_{s,t} + \varepsilon_{s,t} \quad \forall t \in \{2003, \ldots, 2016\}. \tag{5}$$

We then compute the time-series average of the slope coefficients, $\hat{\beta}_i = \frac{1}{T}\sum_{t=2003}^{2016} \hat{\beta}_{i,t}$ for $i \in \{1, \ldots, 4\}$, obtained by estimating the equation above at the end of each June between 2003 and 2016. We report these average slope coefficients in Table 9. In the table, we consider both the case in which R/S is the only predictor of link duration, as well as the case in which additional supplier-level characteristics are also included in the projections. For ease of interpretation each characteristic is scaled by its unconditional standard deviation.

The results in Panel A of Table 9 indicate that increases in the intensity of trade credit usage are associated with longer duration supplier-customer links. Specifically, a one standard deviation increase in R/S extends the average link duration by 3.5 months. This effect is statistically significant at the 5% level. Panel A also shows that R/S remains an economically important and statistically significant prediction of link duration even when additional supplier-level characteristics are included in the regressions. For example, when the profitability, investment intensity, and market capitalization of each supplier are also included as explanatory variables, changes in R/S have the largest impact on link duration.

Panel B of Table 9, which focuses on the probability of supplier-customer links breaking, yields a similar conclusion to Panel A. Panel B shows that increases R/S reduce the probability of supplier-customer links breaking. For instance, when R/S is the only supplier-level characteristic included in equation (5), a one standard deviation increase in R/S reduces the probability of a link breaking by 5%. This marginal effect of R/S is not only economically significant, but is also statistically significant at the 1% level. Similarly, when additional predictors are also included in the projections, R/S remains the most economically important and statistically significant predictor of supplier-customer links breaking. A one standard deviation increase in a supplier's R/S (profitability) reduces the probability of links breaking by 6% (4%). Additionally, the marginal effects of a supplier's market capitalization and investment intensity on the probability of a supplier-customer link breaking are statistically indistinguishable from zero.

Taken together, the results in this section show that a production network characteristic – the average duration of supplier-customer links – can explain the counterparty premium. Although neither common empirical asset-pricing models nor a host of key characteristics from CRSP/Compustat explain the R/S spread (recall Table 2 and Section 3.5, respectively), controlling for link duration subsumes the counterparty premium (recall Table 8). Furthermore, Table 9 shows that increases in R/S increase link duration and reduce the probability of supplier-customer links breaking. This suggests that suppliers' trade credit policies can shape the structure of production networks by influencing the persistence of supplier-customer links.

In the next section, we build a quantitative investment-based asset-pricing model to jointly explain the two prominent empirical facts: (1) low R/S firms have higher returns, and (2) higher receivables implies a lower probability of a supplier-customer link breaking.

5 The model

In this section, we outline a discrete-time model with infinite horizons that embeds trade credit into a production framework. There is a continuum of supplier firms, each offering trade credit to its counterparty – a customer firm. The customer firm is of heterogeneous quality, with a better customer increasing the revenue produced by the supplier firm. Meanwhile, the customer firm is also subject to idiosyncratic liquidity shocks and may default. This default probability can be reduced by the supplier firm providing more trade credit, which acts as insurance against the liquidity shock. We present the details below.

5.1 Production, technology, and investment

Consider a supplier firm i, whose production in period t follows:

$$Y_{it} = (A_t C_{it})^{1-\alpha} K_{it}^{\alpha}, \tag{6}$$

where K_{it} is the level of its physical capital, A_t denotes the level of aggregate productivity, and C_{it} is an idiosyncratic component that captures the quality of the current customer of firm i. Note that we depart from the standard literature by assuming C_{it} is (at least partially) determined by the productivity of a firm's current customer (counterparty). One can think of C_{it} as the productivity of the supplier-customer pair. There is ample evidence of productivity spillovers or synergy created during the production process, and we provide evidence along this line in Section 6.3.2. Alternatively, one can treat the output of the supplier firm as a distinct input good used by the customer firm and therefore not perfectly substitutable. In such case, C_{it} may also capture a customer-specific markup that the supplier charges for selling a specialized product.

The logarithm of the aggregate productivity follows a random walk process with drift μ_a and volatility σ_a

$$\log A_{t+1} = \log A_t + \mu_a + \sigma_a \varepsilon_{t+1}^a, \tag{7}$$

where ε_{t+1}^a is an *i.i.d.* standard Normal shock. By contrast, the evolution of C_{it} depends on whether the customer experiences an idiosyncratic liquidity shock at the beginning of the next period, as we describe in the next subsection.

A fixed operating cost in production, ξK_{it}, is incurred in each period. This cost captures the existence of fixed outside opportunities for capital, which is why the cost scales with the level of a firm's physical capital. Moreover, the firm also chooses investment I_{it} so that capital accumulates according to

$$K_{it+1} = (1-\delta) K_{it} + I_{it}, \tag{8}$$

where δ is the depreciation rate. By increasing the capital stock by I_{it} units, the firm incurs a total cost of $I_{it} + K_{it}\phi(I_{it}, K_{it})$, where:

$$\phi(I_{it}, K_{it}) = b\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 \tag{9}$$

is the adjustment cost incurred in capital investment.

5.2 Counterparty and trade credit

A good counterparty – captured by a high value of C_{it} – helps boost the output produced by the supplier, Y_{it}. However, counterparties may experience liquidity shocks and default for various reasons. Motivated by the empirical evidence, we assume firm i's current counterparty may be subject to a liquidity shock (and fail) at the beginning of the next period $t+1$ with probability:

$$\Gamma(r_{i,t+1}) = \left(\bar{p} - \underline{p}\right)(1 - r_{i,t+1})^{\lambda} + \underline{p}, \tag{10}$$

where $\left\{\bar{p}, \underline{p}\right\}$ are the maximum and minimum default probability, respectively. $r_{i,t+1}$ is the amount of trade credit extended by firm i to its customer in period t, to be repayed in period $t+1$. Choosing $r_{i,t+1}$ is at the discretion of firm i. It takes the form of accounts receivable due in period $t+1$, scaled by the total amount of sales accomplished in period t (i.e., R/S). By construction, $r_{i,t+1}$ varies between 0 and 1. By offering more accounts receivable, firm i provides more liquidity to its customer, and reduces the probability that its counterparty defaults (i.e., $\Gamma_r(r_{i,t+1}) < 0$), similarly to Cunat (2006). λ is a convexity parameter that determines the rate at which the default probability drops with $r_{i,t+1}$.

If the current customer of firm i does not experience a liquidity shock at the beginning of the next period $t+1$, which happens in probability $1 - \Gamma(r_{i,t+1})$, the current customer pays back to firm i the trade receivable account $r_{i,t+1}Y_{i,t}$, and persists to the next period, implying:

$$C_{i,t+1} = C_{i,t}. \tag{11}$$

Otherwise, the current customer defaults. In this case, firm i cannot recoup its accounts receivable, and needs to search and rematch with a new counterparty. The new counterparty's quality is drawn from an i.i.d. pool such that:

$$C_{i,t+1} \sim \mathcal{N}\left(0, \sigma_c^2\right). \tag{12}$$

The search for a new counterparty involves frictions. Specifically, in order to search and rematch with a new customer, firm i needs to pay a predetermined cost $f_t A_t$ at the beginning of the next period (when matching occurs). Note that for stationarity purposes, we assume that the cost of drawing a new counterparty is proportional to A_t. The cost of finding a new counterparty is also subject to a systematic shock f_t that is orthogonal to productivity. Specifically, we assume that:

$$f_{t+1} = f_0 + \sigma_f \varepsilon_{t+1}^f, \tag{13}$$

where ε_{t+1}^f is an i.i.d. standard Normal shock that is independent of ε_{t+1}^a. This shock, which represents a systematic counterpart risk in our model, captures fluctuations in the cost of finding counterparties and establishing collaborations. Such costs include fluctuations in firm entry and regulatory costs. We provide further interpretations for this cost in Section 6.3.1.

5.3 Firm's problem

The firm takes as given the stochastic discount factor (SDF) $M_{t,t+1}$ used to value cash flows in period $t+1$. We specify the SDF as a function of the two aggregate shocks in the economy:

$$M_{t,t+1} = \frac{\beta \exp\left(-\gamma_{a,t}\sigma_a \varepsilon_{t+1}^a - SGN \cdot \gamma_f \sigma_f \varepsilon_{t+1}^f\right)}{\mathbb{E}_t\left[\exp\left(-\gamma_{a,t}\sigma_a \varepsilon_{t+1}^a - SGN \cdot \gamma_f \sigma_f \varepsilon_{t+1}^f\right)\right]}. \tag{14}$$

In the SDF above, γ_f is the magnitude of the price of risk of the counterparty factor's shocks ε_{t+1}^f, and SGN is the sign of its market price of risk. $\gamma_{a,t}$, which is the risk price of aggregate productivity shocks ε_{t+1}^a, is positive and its magnitude is time-varying:

$$\gamma_{a,t} = \exp\left(\gamma_a \sigma_a \varepsilon_t^a\right). \tag{15}$$

When $\gamma_a < 0$, the price of risk for aggregate productivity shocks varies countercylically. The precise mechanism underlying this well-documented countercyclical variation can be, for example, time-varying risk aversion, as in Campbell and Cochrane (1999), or countercylical stochastic volatility. Note that we have normalized the SDF so that the risk-free rate is always equal to the constant $\frac{1}{\beta} - 1$.

We define $\hat{D}_{it}$ as the immediate sales proceeds net of all operating and investment costs:

$$\hat{D}_{it} = Y_t \left(1 - r_{it+1}\right) - \xi K_{it} - I_{it} - \phi\left(I_{it}, K_{it}\right) K_{it}. \tag{16}$$

With probability $\Gamma\left(r_{it+1}\right)$, the current counterparty defaults, and firm needs to pay an additional cost $f_t A_t$ next period to draw a new counterparty. Therefore, the dividends paid to shareholders during period t are case dependent. If the counterparty from the previous period defaults at the beginning of period t, then:

$$D_{it} = \hat{D}_{it} - f_{t-1} A_{t-1}. \tag{17}$$

Otherwise, the firm recoups the accounts receivable extended during period $t-1$:

$$D_{it} = \hat{D}_{it} + Y_{t-1} r_{it}. \tag{18}$$

Let us define $V\left(K_{it}, C_{it}, A_t, f_t, R_{it-1}, \iota_{it}\right)$ as the cum-dividend market value of the firm, where $R_{it-1} = r_{it-1} Y_{it}$ is the level of accounts receivable extended during period $t-1$ and ι_{it} is an indicator function implying whether firm i's counterparty from period $t-1$ has defaulted at the beginning of period t. Firm i chooses investment and account receivable policies to maximize its market value

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

6 Theoretical results

6.1 Calibration

Table 10 shows the calibration of the model parameters. We set the drift parameter, μ_a, and standard deviation parameter, σ_a, of aggregate productivity to match mean and volatility of aggregate output. The parameter σ_c governs the cross-sectional heterogeneity of potential counterparties' quality, and impacts output's idiosyncratic volatility in the model. We set this parameter to 0.6, to target the firm-level volatility of sales growth, which is about 30% per year. Because receivables in the model hedge firms from having to pay a re-matching costs, the parameters governing the matching cost dynamics are tightly linked to moments of the firm-level R/S policy. We set the mean (volatility) of matching cost shocks, f_0 (σ_f), to target the mean (standard deviation) of firm-level R/S of 23% (9%).

We set the depreciation rate, δ, to 8%, and capital share of output, α, to 0.4. Both are standard in the literature and consistent with the data. The quadratic capital adjustment cost, b, is set to 0.9, in order to target the volatility of firm-level investment rates in the data of about 13%. The fixed cost ξ creates a wedge between firms' sales and their operating income, and yields an operating leverage. Thus, we set ξ to 2 in order to match the model-implied volatility of operating profits to sales ratio closely to the data.

The parameters governing the liquidity function, $\overline{p}, \underline{p}$, and λ determine the model-implied duration of supplier-customer links, and its distribution. Empirically, we find that the average supplier-customer duration of low, medium, and high R/S firms is 3.03, 3.69 and 3.98 years, respectively (recall Table 7). We set the former three parameters to target these cross-sectional properties of links' duration within a model-simulated portfolio sort exercise. Specifically, while $\underline{p}$ ($\overline{p}$) is tightly related to the longest (shortest) model-implied duration, the convexity parameter λ is related to the median duration.

Lastly, we set the time-discount rate β to target a constant risk free rate of 2.1% per annum. There are two prices of risk parameters, γ_a and γ_f. We set these parameters such that the mean and volatility of the model-implied equity premium are 7.7% and close to 15%, respectively, as in the data. The former parameter mainly impacts the volatility of risk premia, as it induces time-varying prices of risk, while the latter parameter mainly impacts the level. The sign of the market price of risk of counterparty shocks (SGN) is negative, consistent with the empirical evidence in Table 3.

Model Fit for Aggregate and Firm-Level Moments. Panel A of Table 11 shows model-implied aggregate moments against their empirical counterparts. The model-implied growth rate of aggregate output, as well as the equity premium mean and volatility are successfully targeted by the calibration. The model-implied volatility of aggregate output is just above 2%, and smaller than the data. We deliberately set this volatility to a conservative value such that the model-implied volatility for aggregate consumption (dividend) aligns with the data. The model-implied Sharpe ratio is precisely 50% in both the model and the data. While not directly targeted, the autocorrelation of aggregate output in the model is 0.3, close to the data estimate of 0.22.

Panel B of Table 11 shows both model-implied and data moments for firm-level quantities. The firm-level average of R/S is 23% in the data versus 20% in the model. The firm level volatility of R/S is about 9% in the data and 10% in the model. While both of the former moments are targeted by the calibration, the model also closely matches the firm-level autocorrelation of R/S, without explicitly targeting this moment by the calibration parameters. The model-implied mean of firm-level investment is 14%, which matches the data.

Nonetheless, the autocorrelation of investment rate is somewhat higher than the empirical counterpart. The firm-level volatilities of sales growth and of the ratio of operating profits to sales are both consistent with the data. The former is 30.2% in the model and 33.8% in the data, and the latter is 13% in the model versus 11.1% in the data.

6.2 R/S-sorted model-implied portfolios

Using simulated model data on 5,000 firms for 10,000 periods we sort firms into portfolios based on R/S, in an identical fashion to the empirical procedure described in Section 3. The low (high) portfolio include firms in the bottom (top)decile of the cross-sectional distribution of R/S distribution in every period. Panel C of Table 11 shows moments of these R/S-sorted portfolios within the model and the data.

Our empirical analysis yields two facts. First, high R/S firms have a considerably lower risk premium. Second, high R/S firms maintain longer duration links with their customers. Both facts are replicated by the model. The model implied return spread between low and high R/S firms is 6.8% per annum in the data versus 4.7% per annum in the model. While the model-implied figure is somewhat lower than the data's point estimate, the model-implied spread is within the bounds of the spread's empirical confidence interval. Moreover, the expected duration of a supplier-customer link for low (high) R/S firms is 3.03 (3.88) years in the model which is very close to the data's estimate of 3.03 (3.98) years.

The intuition behind the R/S spread and the duration differences in the model is as follows. The left panel of Figure 1 shows the model-implied firms' policy for extending trade credit. The relation between R/S and the counterparty's quality is positive and monotonic. The higher the quality of the counterparty, the higher the supplier's incentive to keep the same customer going forward. This implies that the hedge that firms provide to their customers in the form of accounts receivable should increase with customer quality. The right panel of the figure also shows that higher quality counterparties endogenously face lower probabilities of a liquidation event. In contrast, the supplier firm does not extend any trade credit to a customer if its quality is sufficiently low. This is because the supplier hopes a liquidity shock will cause its current customer to default, allowing the firm to draw a new customer from the pool of potential counterparties. This policy of extending no trade credit to a low quality customer is optimal for the supplier because reversion to the mean suggests that the expected quality of a new customer exceeds the low quality of the current customer. In all, higher receivables can proxy for the underlying (unobserved) quality of the customer.

The likelihood that an existing supplier-customer link will survive into the following period is the complement to the endogenous default probability of the customer. Because firms with low R/S provide only a small hedge to their customers, the customers of low R/S firms have a higher default probability. Thus, the likelihood that low R/S firms will have the same customer in the next period is lower. In other words, the expected customer-link duration is smaller for lower R/S firms, as shown in Table 11. This suggest that firms with low R/S are more adversely affected by shocks that increase the re-matching cost f, as these low R/S firms are more likely to pay the cost next period. Collectively, this implies that $\beta_f^{R/S=LOW} < \beta_f^{R/S=HIGH} < 0$.

As discussed above, firms with low R/S are endogenously matched (on average) with lower quality customers. This suggest that, all else equal, the sales of low R/S firms are lower than the sales of high R/S firm (recall the production function represented by equation 6). Since the fixed cost ξ does not scale proportionately with sales (or, alternatively, with the counterparty's quality and/or aggregate productivity), operating leverage is created. With lower sales, the degree of operating leverage is higher for low R/S firms. Any change in the aggregate productivity has a larger impact on the profitability of low R/S firms compared to high R/S firm. Overall, low R/S firms are more exposed to fluctuations in aggregate productivity than high R/S firms, which implies that $0 < \beta_a^{R/S=HIGH} < \beta_a^{R/S=LOW}$.

Following the discussion above, the spread between low and high R/S firms, or the counterparty premium, can be written as:

$$Prem = \underbrace{\left(\beta_f^{R/S=LOW} - \beta_f^{R/S=HIGH}\right)}_{(-)} \gamma_f \sigma_f^2 + \underbrace{\left(\beta_a^{R/S=LOW} - \beta_a^{R/S=HIGH}\right)}_{(+)} \gamma_{a,t} \sigma_a^2. \tag{19}$$

Since in both the model and the data, the price of risk of aggregate productivity shocks is positive, $\gamma_{a,t} > 0$, while the price of risk of counterparty shocks is negative, $\gamma_{f,t} < 0$, the overall counterparty premium is positive.

Sensitivity Analysis. Table 12 shows how the counterparty premium changes with two leading model parameter. First, column (3) of the table shows that if the market price of risk of counterparty shocks, γ_f, is zero, the spread is still positive but small in magnitude. The sign of the spread remains positive because the second term in equation (19), which is positive. The fact that the spread falls sharply suggests that most of the counterparty premium in the model (about 98%) is explained by the counterparty (matching) factor. Second, column (4) of the table shows that when the sign of the market price of risk for rematching shocks is switched to positive ($SGN = 1$), the counterparty premium turns negative. This can be seen from the dominant first term in equation (19). Because we set $\gamma_f > 0$, while $\beta_f^{R/S=LOW} - \beta_f^{R/S=HIGH} < 0$, the first term becomes negative and lowers the premium.

6.3 Discussion on the model's assumptions and implications

This section provides a discussion on the model's assumptions and implications. Section 6.3.1 discusses several interpretations of the counterparty factor, while Section 6.3.2 empirically evaluates a key model assumption and a key prediction, related to the the relation between customers' quality and suppliers' cash flows. Finally, we note that our model focuses on suppliers operating within a given layer of the production network (i.e., fixed upstreamness). Hence, to tighten the link between the model-implied counterparty premium and the data, Section 6.3.3 empirically shows that the counterparty premium exists *within* both downstream and upstream production layers, as the model suggests.

6.3.1 Interpretation of the counterparty risk factor

In our model, the counterparty risk is incorporated in the form of a cost that a supplier has to incur in order to search for and be match with a new trade counterparty (customer). Motivated by the empirical evidence in Section 3.3, shocks to this cost have a negative price of risk in the SDF. The search/match cost aims to capture, in a reduced form, frictions that are involved in finding a trade partner that may vary cyclically. In this section, we offer several interpretations for this matching cost. We offer multiple plausible explanations for how such a cost can arise under a general equilibrium setup, and why the underlying frictions that produce the match cost increase the marginal utility (i.e., are priced negatively).

First, the frictions involved in the search for a new counterparty can rise when the pool of potential customers shrinks. When fewer customers are looking for a supplier, it may take longer for a supplier longer to find a trade partner. This implies a more costly search process. The pool of potential customers can shrink, for example, because of a drop in the number of newly created firms that are naturally in search for a supplier.[9] A drop in the number of new establishments is also likely to induce a negative price of risk. New entrants represent young firms with many growth opportunities. A drop in the cohort of new firms can significantly and persistently reduce the growth of the economy, leading to a drop in welfare, and to a negative market price of risk.

Second, an increase in the cost of matching may reflect an increase in the competition level among suppliers. Several unmodeled factors can affect the degree of market power for

[9] In untabulated results we show that the portfolio of firms with low R/S is more negatively exposed to a measure that captures a drop in the number of entrants, compared to the portfolio of firms with high R/S. The measure is constructed as the negative of the ratio between new establishments births to total number of establishments from the BLS. The exposure (beta) is recovered from a regression of portfolio returns on the former measure and aggregate TFP growth from the Federal Reserve Bank of San Francisco.

supplier firms in the model, such as the degree of substitutatbility between their products, lower entry barriers, or a rise in the marginal costs of production. When suppliers have lower market power, a potential customer has, in relative terms, more bargaining power, and can squeeze more rents (favorable terms) from the supplier firm. Marketing costs may also increase to attract a potential client. In a reduced form manner, these forces can manifest as a higher matching cost. An increase in the degree of competition among suppliers can lead to a negative price of risk because of displacement risk. As new supplier firms enter, or innovate, incumbent supplier firms experience a drop in sales. This leads to lower consumption of existing business owners. A rise in the dispersion of marginal utility among consumers can lead to a negative price of risk.

Third, it may be more costly to establish a sustainable link with a potential customer because of changes in regulation and contracting standards. Legal expenses, due diligence expenses, and customer protection laws can all raise the cost incured by the supplier firm. This can, for instance, inhibit the number of connections in the economy, and increase the concentration of the production network leading to lower output and a negative price of risk (see, e.g., Herskovic (2018)).

Fourth, since the matching cost is payed by the supplier firm exactly when its current customer experiences a liquidity shock, this coincides with states of the world in which the customer defaults on existing trade credit. Thus, the cost can also reflect deadweight loss of default, or loss of a potential interest rate payment from the customer to the supplier. These costs reduce the profits of supplier firms that flow to owner consumers, thereby leading to a reduction in welfare, and a negative price of risk.

Overall, the counterparty risk can relate to entry risk, competition risk, regulation risk and other possible frictions involved in a search process. In the model of Section 5 we refrain from explicitly endogenizing the search friction, both for simplicity, and because the friction may stem from multiple sources simultaneously, as suggested by the discussion above. We leave the exercise of modeling a full general equilibrium that incorporates all or some of the above frictions to future research.

6.3.2 Evaluating the relation between customer quality and supplier cash flows

In this section we empirically evaluate one of the model's key assumptions and one of the model's key predictions using supplier-customer relationship data from the FactSet Revere database. On the one hand, a novel feature of our model is the assumption that a supplier's productivity is positively correlated with its customer's productivity (recall the Cobb-Douglas production function represented by equation (6)). On the other hand, a key prediction of our model is that supplier's endogenously choose to extend more trade credit to higher quality customers (recall the policy functions displayed in Figure 1). Thus, our model predicts a positive correlation between a supplier's trade credit usage and its customer's productivity. Below, we examine these correlations empirically, and show that both are in line with the model.

We compute the correlations between supplier-level (denoted by s) and customer-level (denoted by c) characteristics using Fama-MacBeth regressions. Specifically, we compute $\rho(y_c, x_s)$, the correlation between characteristics x_s and y_c as follows. First, in June of each year beginning in 2003, data from the FactSet Revere database (described in Section 4) is used to identify the set of active supplier-customer relationships. Next, the following cross-sectional regression is estimated in each June beginning in 2003 and ending in 2016:

$$y_{c,t} = \alpha + \rho_t x_{s,t} + \varepsilon_{c,t}, \quad \forall t \in \{2003, \ldots, 2016\}. \tag{20}$$

Each supplier-customer link is treated as a distinct observation. Additionally, each of the firm-level characteristics underlying the regression are standardized by each variable's unconditional standard deviation. This means that the slope coefficient ρ can be interpreted as the correlation between $y_{c,t}$ and $x_{s,t}$. Finally, we compute the time-series average of the estimated correlation coefficients $\{\rho_t\}_{t=\{2003,\ldots,2016\}}$ obtained by estimating equation (20) each year. The results of this procedure are reported in Table 13.

Panel A of the table reports the correlation between supplier- and customer-level total factor productivity (TFP). We measure TFP using the firm-level productivity measure of Imrohoroglu and Tuzel (2014). In line with our model's assumption, and the Cobb-Douglas production function represented by equation (6), the correlation between customer- and supplier-productivity is positive, and statistically significant at the 5% level.

Next, Panel B of the table computes the correlation between supplier-level R/S and customer-level TFP. The results show that this correlation is positive and statistically significant at the 1% level. This validates the model's prediction that R/S and customer quality are positive related, as suggested by the model-implied policy functions in Figure 1.

6.3.3 The counterpaty premium across production layers

The real economy features suppliers and customers that are organized in a complex network that features multiple layers of production (e.g., intermediate and final goods producers). However, in the interest of parsimony, our model focuses on a single layer of the production network only (i.e., only suppliers with fixed upstreamness). This means we do not explicitly model the association between a given supplier and its own set of suppliers. To ensure that our model is consistent with the data, Table OA.2.7 in the Online Appendix examines the magnitude of the counterparty premium *across* layers of the production network. The table shows that regardless of whether we focus on more upstream or downstream firms, the counterparty premium is consistently positive and statistically significant across the terciles of upstreamness. Importantly, the weighted-average R/S spread across the upstreamness terciles is 0.57% per month,[10] or approximately 6.8% per annum. Thus, although our model only focuses on a single layer of production, the resulting model-implied spread is consistent with the weighted-average counterparty premium *across* the multiple layers of production in the data.

7 Conclusion

In this paper we examine the relation between trade credit, supplier-customer link duration, and stock returns. We document three novel facts. First, low R/S firms earn a higher risk premium. We term this spread between the returns of low and high R/S firms the trade counterparty risk premium. The counterparty premium is not only unexplained by common asset-pricing factors and accounting characteristics, such as value and investment, but also crowds out the accruals premium. A novel asset-pricing factor based on the counterparty premium is priced negatively in stock returns. Second, low link duration firms earn a higher risk premium. The return spread between low and high link duration firms is economically large and amounts to 0.98% per month. This duration premium can account for the variation in the counterparty premium. Third, R/S is an economically important and statistically significant predictor of the average duration of supplier-customers links. Specifically, supplier's that extend more (less) trade credit to their customers have longer (shorter) relationships with their customers. Higher R/S reduces the probability of a supplier-customer link breaking.

We then construct a production model with trade credit to explain the counterparty premium jointly with the link duration effect. In the model suppliers are matched with customers with heterogeneous quality. The customer may experience a liquidity shock and default on its outstanding debt. Suppliers can extend credit to provide liquidity to the customers, thereby reducing the probability of a default event. If there is no default, the link with the customer persists. Otherwise, the supplier searches for a new customer, and

[10]To see this, note that $0.57 = \frac{1}{3} \times 0.4 + \frac{1}{3} \times 0.83 + \frac{1}{3} \times 0.48$.

pays a stochastic rematching cost.

The model quantitatively matches the counterparty premium to the data. Low R/S firms are riskier for two primary reasons. First, low R/S firms are more likely to search for a new customer next period, and therefore have a larger exposure (in absolute value) to systematic shocks that govern the cost of searching for and matching with a new counterparty. Second, low R/S firms are, on average, matched with lower quality customers. Consequently, low R/S firms have higher operating risks than high R/S firms that are typically matched to more productive customers. The model delivers the prediction that low R/S firms have lower link duration with their counterparty.

Our framework models in reduced form the frictions associated with searching and rematching with a trade counterparty. We discuss possible interpretation for these systematic shocks. Higher systematic rematching cost can relate to a drop in the pool of potential customers such as a smaller cohort of new firms, to an increase in the competition among suppliers, to an increase in regulation and contracting standards, and/or to deadweight costs of default. An interesting direction for future research is to model some of the mechanisms above in a general equilibrium setup, and engogenize the price of risk of counterparty shocks.

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Tables and Figures

Table 1: Portfolios sorted on R/S

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio, as well as the spread between the returns of the low and high R/S portfolios. The sorting variable is defined as $R/S = \frac{\text{Trade Receivables}_t}{0.5\times(\text{Sales}_t+\text{Sales}_{t-1})}$, and the low (high) R/S portfolio includes all firms with R/S below (above) the $10th$ ($90th$) percentiles of the cross-sectional distribution of R/S from fiscal years ending in calendar year $t-1$. Both value- and equal-weighted portfolio returns are reported. 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 2016 and are rebalanced annually. Consequently, portfolio returns span July 1978 to December 2016.

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.182	5.006	1.227	6.379
Medium	1.058	4.528	1.306	6.077
High R/S	0.615	6.418	0.544	7.913
Spread	0.567	4.440	0.683	3.769
(L-H)	(2.52)		(3.27)	

Table 2: Value-weighted R/S spread and factor models
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. 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) three-factor model, while MOM is the momentum factor of Carhart (1997). RMW and CMA correspond to the profitability and investment factors of the Fama and French (2015) five-factor model. Finally, I/A and ROE denote the investment and profitability factor in the Hou et al. (2015) q-factor model. Parentheses report Newey and West (1987) robust t-statistics, and the adjusted-R^2 of each regression is reported in the final row of the table. Returns span July 1978 to December 2016 for all regressions except that involving the q-factor model in column (5). Since our q-factor data ends in December 2015, the q-factor alpha is computed using monthly excess returns that range from July 1978 to December 2015.

	(1)	(2)	(3)	(4)	(5)
MKTRF	-0.312	-0.308	-0.306	-0.256	-0.273
	(-6.13)	(-6.03)	(-6.10)	(-5.02)	(-5.00)
SMB		0.035	0.040	0.132	0.161
		(0.47)	(0.53)	(1.64)	(2.44)
HML		0.053	0.056	-0.050	
		(0.56)	(0.60)	(-0.51)	
UMD			-0.032		
			(-0.72)		
RMW				0.367	
				(3.40)	
CMA				0.138	
				(1.06)	
I/A					0.180
					(1.52)
ROE					0.311
					(2.68)
α	0.798	0.775	0.791	0.585	0.498
	(4.07)	(3.97)	(4.01)	(3.06)	(2.55)
R^2	0.112	0.109	0.109	0.142	0.154

Table 3: The market price of trade counterparty risk
The table reports the estimates of the risk factor loadings associated with both the CAPM (in Panel A) and the Fama and French (1993) three-factor model (in Panel B) when each of these models is estimated with and without the trade 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 $\mathbb{E}_t\left[M_t r^e_{i,t}\right] = 0$, 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 either the CAPM or the Fama and French (1993) three-factor model and CPR_t represents the trade 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 17 Fama-French industry portfolios, and (3) the second set of test assets plus 10 investment portfolios and 10 momentum portfolios. 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 2016 is used to estimate each model.

Panel A: Two-factor model						
	25 portfolios		42 portfolios		62 portfolios	
	CAPM	CAPM+CPR	CAPM	CAPM+CPR	CAPM	CAPM+CPR
b_M	3.675	11.433	3.538	5.316	3.431	5.811
$t(b_M)$	(3.15)	(5.30)		(3.07)	(3.07)	(4.66)
b_C		-19.313		-4.506		-5.961
$t(b_C)$		(-4.64)		(-2.96)		(-4.12)
MAE	0.871	0.692	0.871	0.841	0.879	0.813

Panel B: Four-factor model						
	25 portfolios		42 portfolios		62 portfolios	
	FF3F	FF3F+CPR	FF3F	FF3F+CPR	FF3F	FF3F+CPR
b_M	3.988	9.294	4.042	5.289	3.952	5.807
$t(b_M)$	(3.14)	(4.66)	(3.29)	(3.85)	(3.36)	(4.46)
b_S	1.488	2.423	0.372	0.980	0.180	0.932
$t(b_S)$	(0.87)	(1.28)	(0.22)	(0.57)	(0.11)	(0.55)
b_H	6.374	4.484	4.991	4.719	4.384	3.907
$t(b_H)$	(3.62)	(2.21)	(2.85)	(2.71)	(2.52)	(2.26)
b_C		-14.692		-3.710		-5.294
$t(b_C)$		(-3.86)		(-2.42)		(-3.64)
MAE	0.608	0.481	0.728	0.700	0.775	0.734

Table 4: 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 2016. Details on the construction of each variable are provided in Section OA.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	0.02	0.15	0.56	-0.55	
ln(Size)	8.51	8.99	8.34	0.17	(1.07)
B/M	0.42	0.51	0.50	-0.08	(-1.62)
Asset growth	0.15	0.13	0.20	-0.05	(-1.56)
Momentum	0.23	0.21	0.21	0.02	(0.84)
IVOL	1.46	1.31	1.62	-0.16	(-1.82)
ROA	0.07	0.08	0.02	0.05	(10.89)
Accruals	-0.04	-0.04	-0.02	-0.02	(-4.72)
Leverage	0.23	0.21	0.35	-0.11	(-9.47)
Hadlock-Pierce	-3.92	-4.07	-3.87	-0.05	(-0.71)

Table 5: Controlling for profitability and IVOL: 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 (IVOL), 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 2016.

Panel A: Controlling for ROA				
	Low ROA	Medium	High ROA	
Low R/S	-0.17	1.20	1.28	
Medium	0.39	1.08	1.08	
High R/S	-1.23	0.75	0.66	
Spread	1.06	0.46	0.62	Joint test
(L-H)	($p=0.01$)	($p=0.01$)	($p=0.02$)	($p=0.01$)
Panel B: Controlling for IVOL				
	Low IVOL	Medium	High IVOL	
Low R/S	1.27	1.23	0.22	
Medium	0.96	1.10	0.35	
High R/S	1.04	0.58	-0.93	
Spread	0.23	0.64	1.15	Joint test
(L-H)	($p=0.15$)	($p=0.00$)	($p=0.02$)	($p=0.01$)

Table 6: Controlling for accruals: double-sort analysis

The table reports value-weighted portfolio returns obtained from a conditional double-sort procedure, where in Panel A the control variable (i.e., the first dimension sorting variable) is a firm's total accruals, and the second-stage sorting variable is a firm's receivable to sales (R/S) ratio. The sorting is conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of accruals using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of accruals from the fiscal year ending in calendar year $t-1$. Second, with each of these accruals-sorted portfolios, 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. In Panel B the order of the sorting procedure is reversed. The last two rows in Panel A (Panel B) show the R/S (accruals) spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. Each panel also reports the p-value from a joint test on the null hypothesis that the R/S (accruals) spread across all three (accruals) (R/S) sorted portfolios in Panel A (Panel B) is zero. The sample period is from July 1978 to December 2016.

Panel A: Controlling for accruals				
	Low Accruals	Medium	High Accruals	
Low R/S	1.19	1.24	0.94	
Medium	1.14	1.08	0.66	
High R/S	1.17	0.64	0.43	
Spread	0.02	0.61	0.51	Joint test
(L-H)	($p = 0.49$)	($p = 0.00$)	($p = 0.08$)	($p = 0.03$)

Panel B: Controlling for R/S				
	Low R/S	Medium	High R/S	
Low Accruals	1.47	1.16	0.73	
Medium	1.20	1.08	0.52	
High Accruals	1.06	0.74	0.19	
Spread	0.41	0.42	0.53	Joint test
(L-H)	($p = 0.19$)	($p = 0.03$)	($p = 0.11$)	($p = 0.19$)

Table 7: Network-related characteristics of the R/S portfolios
The table shows the value-weighted network-related characteristics of the portfolios sorted on the trade receivables to sales (R/S) ratio. The sample period underlying this table spans June 2003 to 2016, due to the fact that the FactSet Revere database is only available beginning in April 2003. Details on the construction of each variable are provided in Section OA.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)
Centrality	0.31	0.44	0.44	-0.12	(-0.94)
Upstreamness	1.66	2.74	3.07	-1.41	(-11.08)
N(Customers)	3.46	14.19	9.22	-5.75	(-4.41)
Duration	38.84	46.76	47.33	-8.49	(-2.92)

Table 8: Controlling for duration and number of customers

The table reports the average monthly value-weighted portfolio returns obtained from univariate and conditional portfolio double-sort procedures related to the average duration of each supplier's links with its customers and the average number of customers per supplier. Panel A conducts univariate portfolio sorts in which the cross-section of firms is sorted three portfolios based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of duration (left columns of the table) or number of customers (right columns of the table) at the end of the previous month. Mean refers to the average monthly return, and SD denotes the standard deviation of monthly returns. The spread between the low (L) and high (H) portfolios is also reported. Panel B of the table conducts a conditional portfolio double-sort procedure in which the control variable is the average duration of each supplier's links with its customers, and the second-stage sorting variable is a firm's receivables-to-sales (R/S) ratio. The sorting is conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of duration using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of duration from month $t-1$. Second, within each of these duration-sorted portfolios, 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 $t+1$, when all portfolios are rebalanced. Parentheses in Panel A (Panel B) report t-statistics (p-values) computed using Newey and West (1987) robust standard errors. Panel B 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 2003 to December 2016.

Panel A: Univariate sorts					
	Duration			Num. customers	
Portfolio	Mean	SD		Mean	SD
Low (L)	2.005	2.005		0.946	4.095
Medium	0.860	3.795		0.914	3.741
High (H)	1.021	1.021		0.864	4.136
Spread	0.984	2.533		0.082	2.154
(L-H)	(4.26)			(0.50)	
Panel B: Controlling for duration					
	Low Duration	Medium	High Duration		
Low R/S	2.28	0.55	1.47		
Medium	2.13	0.88	0.97		
High R/S	1.23	0.71	0.94		
Spread	1.05	-0.16	0.54	Joint test	
(L-H)	($p = 0.09$)	($p = 0.68$)	($p = 0.17$)	($p = 0.45$)	

Table 9: Predicting the length of supplier-customer links

The table reports the results of Fama-MacBeth regressions that use supplier-level characteristics to predict the average duration of each supplier's link with its customers, measured in months, (Panel A) and the probability that a supplier-customer link breaks (Panel B). These regressions are implemented as follows. First, in June of each year beginning in 2003, data from the FactSet Revere database is used to identify the set of suppliers. Next, a cross-sectional regression that projects one of two measures of suppler-customer link duration on a host of supplier-level characteristics is estimated. Here, the measure of link duration is either (1) the average future duration of each supplier's links with its customers, or (2) an indicator variable that identifies the situation in which the supplier-customer link breaks. The slope coefficients obtained by estimating these regressions at the end of each June between 2003 and 2016 are saved. Finally, the table reports the time-series average of the point estimate associated with each supplier-level characteristic included in the cross-sectional regression. The table also reports the Newey and West (1987) t-statistic associated with this time-series average. Here, the event that Break = 1 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 three years time. Lastly, each supplier-level characteristic is standardized by dividing the characteristic by its unconditional standard deviation.

	Panel A: Future duration		Panel B: Pr (Break = 1)	
Constant	58.43	59.48	0.58	0.57
	(11.20)	(11.00)	(23.34)	(25.78)
R/S	3.57	4.01	-0.05	-0.06
	(2.12)	(2.43)	(-3.38)	(-3.64)
SIZE		-2.13		-0.01
		(-3.49)		(-0.36)
I/K		-3.29		0.01
		(-1.90)		(0.82)
ROA		3.12		-0.04
		(4.54)		(-3.28)

Table 10: Model Calibration

The table shows the parameters of the benchmark model calibration. The model is calibrated at annual frequency.

Parameter	Value	Description
Technology.		
μ_a	2%	aggregate productivity growth rate
σ_a	2.7%	aggregate productivity standard deviation
σ_c	0.6	dispersion of counterparty quality
f_0	0.4	mean of matching cost
σ_f	0.1	standard deviation of matching cost
Capital.		
δ	8%	Capital depreciation rate
α	0.4	Capital share of output
b	0.9	Quadratic adjustment costs parameter
ξ	2	Fixed operating cost
Liquidity.		
$\overline{p}$	0.5	Liquidity probability when $R/S = 0$
$\underline{p}$	0.25	Liquidity probability when $R/S \to \infty$
λ	10	Convexity of liquidity function
SDF.		
β	0.979	Time discount factor
γ_a	-85	time varying (log) price of risk for aggregate shocks
γ_f	7.6	magnitude (log) of price of risk for counterparty shocks
SGN	-1	negative risk price for counterparty shocks

Table 11: Model-Implied Moments against Data

The table shows model-implied moments against their empirical counterpart. Panel A, B and C show moments related to aggregate quantities, firm-level quantities, and R/S sorted portfolios, respectively. All moments are based on model simulated data over 7,000 periods and 5,000 firms. The first 2,000 periods of the simulation are truncated for removing dependence from initial states. The sorting procedure is identical to the empirical strategy described in Section 3. Low (high) R/S firms refers to the bottom (top) 10% of the cross-sectional distribution of receivables to sales.

Moment	Data	Model
Panel A: Aggregate moments		
Agg output growth mean	2.57	2.01
Agg output growth stdev	4.17	2.23
Agg output growth AC(1)	0.22	0.33
Equity premium mean	7.73	7.80
Equity premium stdev	15.46	15.66
Sharpe ratio	0.50	0.50
Panel B: Firm-level moments		
Firm level R/S mean	23.5	20.14
Firm level R/S stdev	8.8	10.18
Firm level R/S AC(1)	0.50	0.45
Firm level I/K stdev	13.40	14.29
Firm level I/K AC(1)	0.48	0.19
Firm level sales growth volatility	30.25	33.82
Firm level operating profits/sales volatility	13.60	11.13
Panel C: R/S-sorted portfolios moments		
Avg return low R/S	14.13	13.30
Avg return mid R/S	12.69	10.38
Avg return high R/S	7.38	8.53
R/S spread	6.80	4.77
Exp link duration low R/S	3.03	3.03
Exp link duration mid R/S	3.69	3.82
Exp link duration high R/S	3.98	3.88

Table 12: Counterparty Premium: Sensitivity Analysis
The table shows model-implied average returns for R/S sorted portfolios and the counterparty premium. The return moments are reported for the benchmark calibration in column (2), as well as for modified calibrations that are identical to the benchmark, except for featuring a zero market price of risk for matching shocks in column (3), or featuring a positive price of risk (with the same absolute value as the benchmark) for matching shocks in column (4).

		Benchmark		
	(1)	(2)	(3)	(4)
Moment	Data	Model	$\gamma_f = 0$	$SGN = 1$
Avg return low R/S	14.13*	13.30	5.106	4.268
Avg return mid R/S	12.69*	10.38	5.045	4.380
Avg return high R/S	7.38*	8.53	5.002	4.420
R/S spread	6.80	4.77	0.104	-0.152

Table 13: Evaluating model assumptions and predictions
The table reports the results of Fama-MacBeth regressions that examine the correlations between supplier- and customer-level characteristics. These regressions are implemented as follows. First, in June of each year beginning in 2003, data from the FactSet Revere database is used to identify all active supplier-customer relationships. Next, the following cross-sectional regressions are estimated. In Panel A, the TFP of each customer is projected on the TFP of each supplier. In Panel B, the TFP of each customer is projected on the receivables-to-sales (R/S) ratio of each supplier. There firm-level characteristics underlying each regression are standardized by dividing each characteristic by its unconditional standard deviation. These cross-sectional regressions are estimated at the end of each June from 2003 until 2016, when the sample ends, and all estimated slope coefficients are saved. Finally, the table reports the time-series average of the estimated slope coefficient underlying each cross-sectional regression. The table also reports the Newey and West (1987) t-statistic associated with this time-series average, as well as the the average adjusted-R^2 from each cross-sectional regression.

	Panel A	Panel B
	$\rho\,(TFP_c, TFP_s) > 0$	$\rho\,(TFP_c, R/S_s) > 0$
ρ	0.022	0.164
	(2.374)	(10.496)

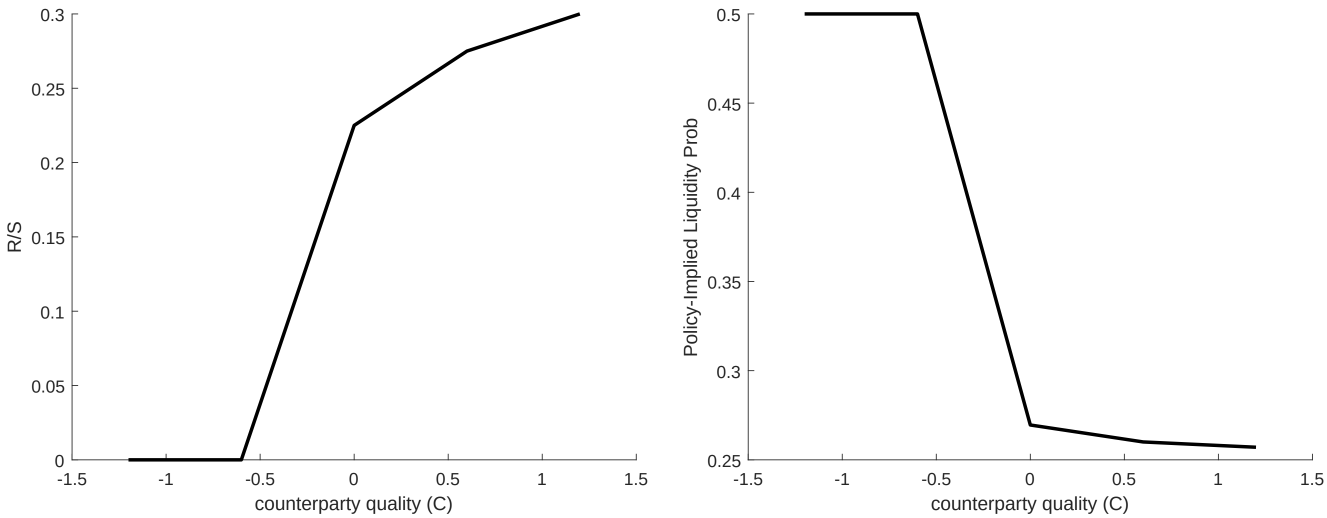

Figure 1: Model-Implied Policy Functions
The left figure shows the model-implied policy for R/S (r) against different values of counterparty quality (C). The right figure shows the liquidity probability (π) for the counterparty as implied by the R/S policy. Both policies are plotted when all other state variables are set to their stochastic steady state values.

A Online appendix

OA.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 $t-1$.

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 2018, 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 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.

Probability of failure (Fail. prob.). We compute the probability of failure for each firm by following the procedure outlined by Campbell et al. (2008).

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 $SA_{i,t} = -0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.040 \times \text{Age}_{i,t}$.

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.

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).

Network 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 et al. (2018).

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 2018, 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.

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. 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 et al. (2018).

Receivables to sales (R/S). Trade receivables to sales is computed as trade receivables (Compustat Annual item RECTR) divided by average total sales (Compustat Annual item SALE) over the last two years.

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

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

OA.2 Supplemental tables

Table OA.2.1: Portfolios sorted on R/S: sub-sample evidence
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 3.2.2, except that the sample period underlying the results in the left-hand (right-hand) panel of the table covers July 1987 to June 1996 (July 1996 to December 2016). 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.

	Sub-sample 1: 197807 to 199606		Sub-sample 2: 199601 to 201612	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.413	5.272	0.979	4.761
Medium	1.344	4.436	0.806	4.601
High R/S	0.821	6.438	0.434	6.407
Spread	0.592	4.328	0.545	4.544
(L-H)	(1.75)		(1.81)	

Table OA.2.2: Portfolios sorted on R/S: quarterly sorts
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 similar to the benchmark analysis, described in Section 3.2.2, except that the sorts are implemented using data from Compustat Quarterly, and the portfolios are rebalanced on a quarterly basis beginning in 2003 due to data availability. 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.

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.180	4.258	1.224	6.494
2	0.981	4.061	1.317	5.961
High R/S	0.635	5.019	0.603	6.466
Spread	0.546	3.952	0.621	3.236
(L-H)	(1.68)		(2.37)	

Table OA.2.3: Portfolios sorted on R/S: alternative breakpoints
The table reports the average monthly returns of five 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 3.2.2, except that portfolio breakpoints are based on the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of R/S are employed. 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 2016.

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.143	4.250	1.262	5.897
Medium	1.055	4.529	1.391	5.972
High R/S	0.868	5.665	0.964	7.114
Spread	0.275	2.811	0.298	2.519
(L-H)	(1.99)		(2.19)	

Table OA.2.4: Transition matrix of constituents between R/S portfolios

The table shows the probability of a firm sorted into portfolio $i \in \{\text{Low, Medium, High}\}$ in year t, where i is the row index, being sorted into portfolio $j \in \{\text{Low, Medium, High}\}$ in year $t+1$, where j is the column index. The transition probabilities are computed using annual receivables to sales data from June 1978 to December 2016. Firms are sorted into portfolios at the end of each June following the portfolio formation procedure described in Section 3.

Portfolio in	Portfolio in year $t+1$		
year t	Low	Medium	High
Low	0.846	0.130	0.023
Medium	0.020	0.954	0.026
High	0.015	0.510	0.475

Table OA.2.5: Equal-weighted counterparty risk premium and factor models

The table reports the results of time-series regressions of the equal-weighted counterparty risk premium (the portfolio that buys low receivables to sales firms and shorts high receivables to sales firms) on a number of common risk factors. 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) three-factor model, while MOM is the momentum factor of Carhart (1997). RMW and CMA correspond to the profitability and investment factors of the Fama and French (2015) five-factor model. Finally, I/A and ROE denote the investment and profitability factor in the Hou et al. (2015) q-factor model. Parentheses report Newey and West (1987) robust t-statistics computed using three lags, and the adjusted-R^2 of each regression is reported in the final row of the table. Returns span July 1978 to December 2016 for all regressions except that involving the q-factor model in column (5). Since our q-factor data ends in December 2015, the q-factor alpha is computed using monthly excess returns that range from July 1978 to December 2015.

	(1)	(2)	(3)	(4)	(5)
MKTRF	-0.285	-0.189	-0.175	-0.088	-0.145
	(-4.95)	(-4.64)	(-4.42)	(-2.29)	(-3.04)
SMB		-0.053	-0.059	0.073	0.088
		(-0.84)	(-0.96)	(1.05)	(1.55)
HML		0.478	0.507	0.216	
		(5.44)	(5.38)	(2.38)	
UMD			0.071		
			(0.90)		
RMW				0.485	
				(4.88)	
CMA				0.504	
				(3.94)	
I/A					0.816
					(7.16)
ROE					0.296
					(2.43)
α	0.867	0.670	0.610	0.343	0.288
	(4.25)	(3.65)	(3.27)	(2.03)	(1.62)
R^2	0.112	0.244	0.249	0.340	0.293

Table OA.2.6: Controlling for 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 fail probability (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 2016.

Panel A: Controlling for fail probability				
	Low Fail prob.	Medium	High Fail prob.	
Low R/S	1.49	1.11	0.50	
Medium	1.17	1.05	0.62	
High R/S	1.27	0.67	-0.87	
Spread	0.21	0.44	1.36	Joint test
(L-H)	($p = 0.18$)	($p = 0.02$)	($p = 0.00$)	($p = 0.01$)
Panel B: Controlling for O-Score				
	Low O-Score	Medium	High O-Score	
Low R/S	1.21	1.21	0.05	
Medium	1.05	1.13	0.62	
High R/S	0.44	0.58	-0.20	
Spread	0.77	0.64	0.25	Joint test
(L-H)	($p = 0.00$)	($p = 0.00$)	($p = 0.32$)	($p = 0.02$)

Table OA.2.7: Controlling for upstreamness: double-sort analysis
The table reports the average monthly value-weighted portfolio returns obtained from a conditional double-sort procedures 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 sorting is conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of upstreamness using the 33^{rd} and 66^{th} percentiles of the cross-sectional distribution of upstreamness from month $t-1$. Second, within each of these upstreamness-sorted portfolios, 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 $t+1$, 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 2016.

	Low upstreamness	Medium upstreamness	High upstreamness	
Low R/S	1.18	1.32	0.94	
Medium	1.15	1.08	0.99	
High R/S	0.78	0.49	0.46	
Spread	0.40	0.83	0.48	Joint test
(L-H)	($p = 0.03$)	($p = 0.00$)	($p = 0.03$)	($p = 0.01$)

OA.3 Model Solution

Let us 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. The value function iteration problem can be formulated equivalently

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

[Model Detrending: To be completed]

OA.4 Numerical model solution

We use a value function iteration to solve the model. We discretize Gaussian shocks using Tauchen. [Grid Specifications: To be completed]