Counterparty Risk:
Implications for Network Linkages and Asset Prices*

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July 19, 2020

Abstract

This paper studies the relation between trade credit, risk, and the dynamics of production network linkages. We find that firms that extend more trade credit earn 7% p.a. lower risk premia, and maintain longer relationships with their customers. We also document that suppliers with longer-duration links to their customers command lower expected returns. We quantitatively explain these facts using a production-based model. Trade credit helps to hedge customers against liquidity risks, thereby reducing suppliers' exposures to costs incurred in finding new customers. Overall, trade credit is informative about the lifespan of supplier-customer links, the production network's density, and macroeconomic risk.

JEL classification: G12, L11, L14, D25

Keywords: Trade credit, receivables, asset pricing, production network

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We thank Hengjie Ai, Ravi Bansal, Michael Barnett, Francesco Bianchi, Anna Cieslak, Ric Colacito, Max Croce, Winston Dou, Maryam Farboodi, Kenneth Judd, Lars-Alexander Kuehn, Ye Li, Peter Pope, Jacob Sagi, Andreas Stathopoulos, Roberto Steri, and Harold Zhang for helpful comments and suggestions, as well as seminar participants and discussants at the University of North Carolina, 3rd Corporate Policies and Asset Prices Conference (COAP), the 8th CIRANO-Walton Workshop on Networks in Economics and Finance, the Indiana University Kelley Junior Finance Conference, the Triangle Macro-Finance Workshop, the 2020 NBER Summer Institute on Capital Markets and the Economy, and the 2020 Stanford Institute for Theoretical Economics (SITE) meeting on Asset Pricing, Macro Finance and Computation. All errors are our own.

1 Introduction

The allocation of credit among economic agents is integral to both production and financial networks: suppliers extend credit to customers, and banks lend to other institutions. The amount of credit a lender extends to a borrower in the network depends on the risk of each agent and the macroeconomy. Consequently, credit should convey important information about firm- and aggregate-level fundamentals. Motivated by this intuition, we study the implications of credit provision for micro- and macro-level risks and for network linkages, using trade credit in production networks as a laboratory.

Trade credit is among non-financial firms' largest sources of short-term financing, and consequently, plays a key macroeconomic role. When selling goods to customers, suppliers typically demand cash for only a fraction of the sales. The rest is sold for credit and logged as accounts receivable. Does offering trade credit increase a supplier's exposure to operating and counterparty risks?[1] How does trade credit relate to macroeconomic risk? Can trade credit provide information on suppliers' trade counterparties (i.e., customers), such as their quality? Do changes in trade credit affect the strength of supplier-customer links, and the production network's density? We address these questions empirically and theoretically.

Our empirical analysis establishes three facts. First, we find that trade credit is an important determinant of firms' risk profiles. Firms that extend more trade credit, and have higher ratios of receivable-to-sales (henceforth R/S), earn a significantly *lower* risk premium. The return spread between low and high R/S firms, which we term the "counterparty premium" is close to 0.60% per month, or above 7% per annum. Second, we find that trade credit impacts the dynamics of supplier-customer links. At the micro-level, high R/S firms have longer duration links to their customers. At the macro-level, aggregate trade credit positively predicts the density of the production network. Thus, the information content of trade credit is valuable for predicting both discount rates and the lifespan (i.e., the duration) of supplier-customer links. Third, to reconcile the first two findings we establish a novel link-duration spread: firms that have longer-lived relationships with their customers command lower expected returns.

[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 accounts receivable (i.e., by extending trade credit to the customer).

In our theoretical analysis we construct a production model to explain the cross-sectional empirical facts quantitatively. By offering more trade credit to a high-quality customer, a supplier implicitly provides liquidity to this firm. This increases the likelihood of retaining this customers in the future, and hedges the supplier against systematic frictions involved in the search for new customers. Thus, a firm that offers higher R/S is safer. We explore economic channels that both generate cyclical fluctuations in the search costs for customers and affect marginal utility, consequently yielding a priced "counterparty" risk factor. These search costs are linked to changes in the birth rate of new firms or the degree of competition among suppliers.

The counterparty premium is puzzling vis-á-vis two hypotheses that posit an ambiguous relation between trade credit provision and risk. On the one hand, offering more trade credit could increase a firm's operating risk. Firms that extend trade credit are exposed to adverse shocks that affect their counterparties. For instance, if the customer is subject to shocks that deteriorate its financial conditions, these shocks can easily spread to the supplier. Moreover, as defaults tend to happen in bad states, these adverse counterparty shocks covary with the cycle. Under this conjecture, high R/S firms are riskier,[2] and should command a higher risk premium.[3]

On the other hand, endogenously riskier firms (e.g., those matched with riskier customers) may choose to extend less trade credit. While this conjecture predicts low risk premia for high R/S firms, consistent with the data, the source of risk (i.e., the type of systematic shock) that renders low R/S firms riskier remains unclear. In particular, we show that the counterparty premium is not explained by common macroeconomic pricing factors. Double-sort analyses and Fama-Macbeth regressions show that trade credit predicts stock returns negatively, controlling for known characteristics, including

[2]This logic is prevalent in financial accounting. Days receivables is a financial ratio that is proportional to R/S, and is widely used to assess the efficiency credit policies. Typically, higher days receivables is interpreted as having larger counterparty risk or lax collection of credit.

[3]Note that the ability of firms to factor previously extended trade credit to a third party can mitigate the exposure to adverse shocks that affect customers. Consistently, we do not find that firms providing more trade credit have higher risk premia. Nonetheless, selling trade credit to a third party does not materially change the role of trade credit as providing liquidity (insurance) to customers. Whether trade credit is sold or not, a customer receiving trade credit is endowed with a liquidity buffer, and if the customer defaults, the supplier must still search for a new customer. As we explain further in Sections 4 and 6, this liquidity-insurance role in conjunction with search costs for new customers, is the key economic channel for reconciling the R/S spread.

profitability, working capital (accruals), and distress.[4] We use a GMM procedure to show that a novel counterparty risk factor increases the marginal utility of investors, and is priced negatively in the cross-section of equities.

To shed light on the drivers of the counterparty premium, we examine firm-level network data on supplier-customer relationships. While common network characteristics, such as centrality, do not explain the premium, we find that low R/S firms have shorter-lived (lower duration) links with their customers. In particular, "horse race" regressions show that R/S emerges as the most powerful predictor of the survival and the length of supplier-customer relationships, which are otherwise hard to observe. At the aggregate level, a one standard deviation increase in average R/S predicts an increase of about 4% in the production network's density. Moreover, we document a cross-sectional spread associated with the duration of supplier-customer links. Suppliers that maintain shorter duration links with their customers earn average returns that are 0.98% higher per month than those earned by suppliers that maintain higher duration links. A double-sort analysis shows that within link-duration portfolios, the R/S spread is insignificant. Thus, differences in link duration can reconcile the counterparty premium puzzle.

We then construct a quantitative model to jointly explain why low R/S firms have both higher stock returns and lower duration links with their customers. In the model, each supplier is matched with a customer of heterogeneous quality, and each supplier's revenue increases with both aggregate productivity and the quality of its customer. The effect of the customer's quality on the supplier's revenue can be interpreted as either (i) a positive spillover from the productivity of the customer to that of the supplier, or (ii) a higher markup the supplier charges its customer for selling a specialized product. In each period, the customer may experience a liquidity shock and default. However, suppliers can partially insure their customers against these liquidity shocks by offering trade credit. More trade credit provides liquidity to the customer, and reduces the probability of the customer defaulting.

In the case that the customer does not experience a liquidity shock, it repays its supplier the previously extended accounts receivable (trade credit), and the link between the two firms persists. In the case that the customer experiences a liquidity

[4] We also find the accruals (working capital) spread is insignificant across R/S-sorted portfolios. This suggests the economic determinants of the counterparty premium may explain the accruals effect.

shock, it cannot repay the trade credit, and thus defaults. Moreover, the supplier has to search for a new customer, which involves non-trivial search frictions. Specifically, the supplier has to pay a search cost that fluctuates systematically to match with a new counterparty. We refer to innovations that increase these common search and rematching costs as "counterparty shocks." While not explicitly modeled, an increase in these costs may capture an aggregate economic state with (i) fewer customer firms looking for suppliers (e.g., the pool of new entrants shrinks, resulting in a harder search), (ii) higher competition among suppliers (e.g., lower bargaining power for suppliers compared to customers), or (iii) increased regulation (e.g., more costly to contract with a customer). We provide empirical support for these interpretations.

Firms that extend more trade credit are endogenously safer in the model for two reasons. First, high R/S firms provide more insurance to their customer against liquidity shocks, increasing the likelihood that the supplier-customer link lasts longer. As a result, high R/S firms are less likely to search for a new customer next period, and have lower exposures (in absolute value) to the systematic counterparty shocks. Put differently, high R/S acts as a hedging device against the costs involved in the search for new customers. Second, high R/S suggests that, all else equal, the firm is currently matched with a better quality customer. This is because firms have a greater incentive to keep (insure) better customers, creating a monotonically increasing relation between a customer's quality and observed R/S. In the model, high quality customers make their suppliers safer. A higher quality customer increases the output of its supplier, and reduces the supplier's operating leverage. Consequently, this drops the supplier's exposure to aggregate productivity shocks. While both channels make high R/S firms safer, the first channel dominates. The model quantitatively matches the counterparty premium, and key investment- and R/S-related moments, to the data.

We empirically examine the characteristics of supplier-customer pairs and verify two of the model's restrictions. First, suppliers indeed extend more trade credit to higher-quality customers. The association between a supplier's R/S ratio and its customer's productivity, as proxied by the firm-level measure of Imrohoroglu and Tuzel (2014), is positive and statistically significant. Second, we document positive and significant association between a supplier's productivity and its customer's productivity. That is, more productive suppliers trade with more productive customers.

Related literature

This study relates to three strands of papers: the literature on production-based asset pricing, the literature on production networks in macroeconomics and finance, and the literature on trade credit's role in corporate finance.

Our paper is related to studies that connect the production decisions of firms to expected returns. To the best of our knowledge, our paper is the first to quantitatively and theoretically examine the implications of trade credit policies for risk premia. Traditional studies in this literature rely on capital adjustment costs (e.g., Berk, Green, and Naik (1999), Boldrin, Christiano, and Fisher (2001), Zhang (2005), Jermann (2010), Croce (2014)) or labor market frictions (e.g., Uhlig (2007), Belo, Lin, and Bazdresch (2014), Belo, Li, Lin, and Zhao (2017), Kilic (2017)) to explain aggregate and cross-sectional risk premia via differential exposures to aggregate productivity.[5] Our study proposes an alternative mechanism: time-varying exposures to systematic frictions involved in the search for potential customers. This mechanism does not rely on capital or hiring frictions. In fact, we show that the contribution of aggregate productivity shocks to the counterparty premium is quantitatively small. While Dou, Ji, Reibstein, and Wu (2019) show that the departure of key talent affects the fragility of supplier-customer links, we highlight that trade credit affects the durability of these links. We also show that the counterparty spread is distinct from related production-based spreads, such as the productivity (Imrohoroglu and Tuzel (2014)), inventory growth (e.g., Belo and Lin (2012) and Jones and Tuzel (2013)), investment (e.g., Titman, Wei, and Xie (2004) and Cooper, Gulen, and Schill (2008)), working capital (Wu, Zhang, and Zhang (2010)), and distress (e.g., Griffin and Lemmon (2002)) premia.

Our findings are also related to recent advances in macroeconomics and finance that associate business cycle and price fluctuations to production networks. In particular, the locations of firms in the production network, and their relations to their peers, can affect firms' risk premia. Ahern (2013) shows that industries with a higher eigenvalue centrality earn higher expected returns, while Gofman, Segal, and Wu (2020) show that upstream firms (those further from final goods produces) earn higher expected returns than downstream firms (those closer to final goods producers). We confirm

[5] Also see, e.g., Eisfeldt and Papanikolaou (2013), Ai, Croce, and Li (2013), Ai and Kiku (2016), Tuzel and Zhang (2017), Ai, Kiku, Li, and Tong (2018), Ai, Li, Li, and Schlag (2019), and Loualiche et al. (2019).

that the counterparty premium is not explained by network centrality, and is positive and significant within all layers of the production network. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) show that a supplier's risk is related to the concentration and idiosyncratic volatility of its customers. We find that there are no differences in either customers' concentration or idiosyncratic volatility between the low and high R/S portfolios. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) examine the predictability of stock returns using supplier-customer links. We show that supplier-customer links are themselves predictable via trade credit.[6]

Other studies on production networks show that the structure of the production network (and the density of its links in particular) can amplify risk, and consequently, affect the marginal utility of households. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) show that sparsity of inter-sector trade inhibits diversification. This leads to the propagation of idiosyncratic shocks, and magnifies aggregate volatility. Gabaix (2011) proposes a "granularity" hypothesis whereby the idiosyncratic shocks of very large firms become systematic, and raise the volatility of aggregate quantities. Herskovic (2018) examines the relation between network structure and aggregate consumption, and shows that network concentration (sparsity) increases (drops) the marginal utility. In these studies, the structure of the production network (i.e., its adjacency matrix) is either static, or changes *exogenously.* In our paper, the duration of supplier-customer links are *endogenously* affected by trade credit. We find that lower credit reduces the expected lifespan of these relationships. This has a macroeconomic implication: lower aggregate trade credit makes the network less dense in the future, by decreasing the number of surviving links. As pointed out by the former studies, this can lead to the amplification of shocks.

In relation to the role of trade credit, a number of studies examine when, and why, suppliers offer credit to customers. Costello (2020) shows that during the 2007-2008 financial crisis, suppliers pass on their liquidity shocks to their customers, who later show a spike in credit risk and a reduction in employment. This story supports our key channel that by offering trade credit, a supplier firm essentially helps the cus-

[6]Other studies that examine the pricing implications of production networks include the works of Buraschi and Porchia (2012); Aobdia, Caskey, and Ozel (2014); Rapach, Strauss, Tu, and Zhou (2015); Branger, Konermann, Meinerding, and Schlag (2018); Ready, Roussanov, and Ward (2017); Ozdagli and Weber (2018); Richmond (2019). However, these studies have not considered the role of trade credit for network dynamics.

tomer hedge against liquidity risk. Relatedly, Garcia-Appendini and Montoriol-Garriga (2013) shows that during the crisis, firms with high pre-crisis liquidity levels increased trade credit extended to corporations that are financially constrained and subsequently experienced better performance. This is consistent with our model. Namely, this evidence is in line both with the view that trade credit acts as liquidity insurance (Cunat, 2006; Wilner, 2000) particularly when bank credit is scarce, and with 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 in line with Meltzer (1960) in regards to 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 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.

The rest of this paper is organized as follows. Section 2 lays out our novel empirical facts, that connect trade credit both to risk (the counterparty premium) and to the duration of supplier-customer links. Section 3 presents the production model used to reconcile these findings. In Section 4, we show the quantitative model results. Section 5 provides a discussion on the model's assumptions, predictions, and implications. In Section 6, we empirically rule out alternative mechanisms for the counterparty premium. Finally, Section 7 provides concluding remarks.

2 Empirical Facts

2.1 Data

Our paper combines several data sources. First, monthly stock return data are taken from CRSP, and 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.[7] 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 6000–6999) and public utilities (SIC 4900–4999). Our analysis ranges from 1978 to 2016 because data on trade receivable is sparse prior to 1978.

Firm-level data on supplier-customer relationships is obtained from the FactSet Revere database. This novel dataset provides comprehensive coverage of inter-firm links using information from a combination of accounting statements, press releases, investor presentations, corporate announcements, and firms' websites. Importantly, by reporting both the start and end date of each supplier-customer link, the FactSet data allows us to measure link duration. The availability of FactSet Revere database allows us to document how trade credit usage is related to the dynamics of these links.[8]

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

[8]The FactSet data is suitable for the study since 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 when inter-firm relationships begin and end with sufficiently high frequency (e.g., Capital IQ and Bloomberg). For example, the FactSet Revere database has over 20,000 supplier-customer links covering 4,000 customer firms in 2003. In contrast, the the Compustat Segment database has fewer than 2,500 supplier-customer links covering fewer than 1,000 customer firms in the same year.

We follow the procedure outlined in Gofman et al. (2020) to clean and link the data to CRSP/Compustat. Suppliers in the sample exclude financial, conglomerates, real estate. We filter the data to ensure that all sampled suppliers trade with more than one customer.

2.2 Fact 1: Trade credit and risk

We examine the empirical relation between trade credit provision and firms' risk profile. We document that firms offering more trade credit to their customers command a lower risk premium, and therefore are safer.

2.2.1 Measuring trade credit provision

We measure the extent of trade credit provision for firm i in year t by scaling the firm's trade receivables by its sales:

$$R/S_{i,t} = \frac{\text{Trade receivables}_{i,t}}{\text{Sales}_{i,t}}. \tag{1}$$

This ratio is often used to assess the effectiveness of a company's credit provision policies,[9] and the company's ability to collect cash from sales made on credit.

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 2016, we sort firms into portfolios based on the value of R/S in the fiscal year ending in calendar year $t-1$.[10] This lag between the release of accounting data and the June sort dates is conservative, but ensures this strategy is tradable. Each portfolio is then held from July of year t to the end of June of year $t+1$, at which point in time all portfolios are rebalanced. This annual rebalancing allows us to capture conditional variation in the intensity of firm-level trade credit usage (and counterparty risk).

We form three portfolios on each 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 year $t-1$. The medium R/S portfolio includes the remaining firms whose R/S ratios fall between these two breakpoints. Section OA.6 of the Online Appendix shows that our results are robust to alternative choices of portfolio breakpoints. The mean firm-level R/S ratio is about 23%. There is a large degree of cross-sectional variation in trade credit provision: the R/S ratio of

[9]This ratio multiplied by 365 is also known as Days Receivables in accounting.

[10]In untabulated results we construct R/S using Compustat Quarterly data, and show that our results are qualitatively similar using a quarterly sort. However, trade receivables data in Compustat Quarterly is very sparsely populated prior to the early 2000s. Consequently, we use Compustat Annual data in our benchmark analysis, which start in the 1970s.

the low (high) R/S portfolio is 2% (50%).[11]

Trade credit provision varies not only cross-sectionally but also over time for each firm. Firms can alter the amount of trade credit they extend to their customers substantially over time. Table OA.6.3 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 60% of firms with high values of R/S continue to offer a relatively large amount of trade credit between years.

2.2.2 The counterparty premium

Table 1 reports the monthly returns of portfolios sorted on R/S. We find 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 1.19% per month. In contrast, the portfolio of firms that extend high amounts of trade credit to their customers earns a value-weighted return of 0.59% per month. Consequently, the value-weighted (equal-weighted) spread between the returns of the low and high R/S portfolios is about 0.58% (0.45%) per month, and is statistically significant at the 1% (5%) level.[12] The annualized Sharpe ratios of the value- and equal-weighted R/S spreads are 0.50 and 0.45, respectively. We label the approximately 7% p.a. difference between the stock returns of low and high R/S firms the *counterparty premium*, since firms with different levels of R/S should have different exposure to adverse counterparty shocks.

We examine whether the counterparty premium is explained by common unconditional factor models. We project 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 shown in Table 2. The table shows that the monthly αs obtained from these projections are always greater than 0.49% per month and statistically significant.[13]

[11]Table 14 in Section 6 offers more detailed characteristics of these R/S-sorted portfolios.

[12]Table OA.6.1 of the Online Appendix verifies that this result persist also only in the second half of our sample period.

[13]The smallest t-statistic associated with the abnormal returns of the R/S spread is obtained when the R/S spread is projected on the q factors of Hou et al. (2015). This finding is consistent with the

Collectively, these results demonstrate that the counterparty premium contains some time-series variation that is orthogonal to the variation in factors such as size, book-to-market ratios, investment intensity, and profitability.

Counterparty premium: a puzzle? The relation between R/S and expected returns is a priori unclear. From the perspective of financial statement analysis, high R/S firms are typically perceived as having low operating efficiency, and as potentially having high exposures to shocks that deteriorate their customers' financial conditions. As defaults tend to happen systematically during economic downturns, high R/S firms could command higher risk premia. However, the fact that they command lower risk premia suggests that high R/S firms are, in fact, *safer* than low R/S firms.

The sign of the counterparty premium supports the hypothesis that endogenously safer firms choose higher levels of R/S. Nonetheless, the relative safeness of high R/S firms is *anomalous* from the perspective of extant factors and known spreads. As previously discussed, common empirical asset-pricing models fail to explain the counterparty premium. Consistently, in Section 2.2.3 we provide evidence that the premium represents a potentially novel factor. To resolve the puzzle, Section 2.3 turns to granular network data on supplier-customer relationships. Furthermore, Section 6 shows that the counterparty premium is not explained by differences in common characteristics.

2.2.3 Trade credit and macroeconomic factors

The time-series variation in the counterparty premium is mostly unrelated to well-established macroeconomic factors. Consequently, counterparty risk may be a distinct determinant for investors' marginal utility and stock prices. We examine this possibility by evaluating whether a counterparty risk factor is priced in the cross-section of stock returns (i.e., impacts the marginal utility of investors).

We undertake this analysis by assuming that the stochastic discount factor (SDF) that prices all assets in the economy is given by

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

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

model in Section 3, which shows that a small component of the counterparty premium is explained by investment risk and operating leverage.

risk factor using the spread between the value-weighted returns of the portfolio that buys high R/S firms and sells low R/S firms.[14] $\boldsymbol{b}$ 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:

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

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.

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). 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, we also consider the case in which b_{CPR} in equation (2) is set to zero. This allows us to examine the degree to which including the counterparty risk factor in the SDF improves the fit of the model (as measured by the decrease in MAE).

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

[14] This spread captures any systematic shocks that make low R/S firms risky. According to our model in Section 3, these systematic counterparty shocks are related to the costs associated with finding new customers. We use the high-minus-low R/S spread to proxy for these shocks since the model in Section 3 suggests that $0 > \beta^{R/S=HIGH}_{CPR} > \beta^{R/S=LOW}_{CPR}$. Thus, shocks to the high-minus-low spread are *positively* correlated with underlying search costs shocks. We discuss the relation of these systematic search costs shocks to the macroeconomy in Section 5.1.

risk factor are consistently negative, and are always statistically significant at the 5% level or better. In particular, if all 62 test assets are included in the estimation, then the market price of counterparty risk in Panel A (Panel B) is -5.8 (-5.3). Each of these prices of risk are significant at better than the 1% level. The table also shows that adding the counterparty factor to the CAPM or the Fama and French (1993) three-factor model can reduce the MAE of these models by as much as 28%.

The GMM evidence suggests that a counterparty risk factor is priced in the cross-section of returns, and carries a negative market price of risk. Notably, an increase in counterparty risk is associated with bad states of the world. This evidence motivates us to empirically track the economic risk that underlie the counterparty factor in Section 2.3. Moreover, it shows clearly that a model with a single aggregate productivity shock should not (and cannot) explain the R/S spread. Consequently, we introduce a systematic counterparty shock to the theoretical framework in Section 3.[15]

2.3 Fact 2: Trade credit and the production network

Trade credit provision involves both a supplier that offers the credit and a customer that promises to repay it. Therefore, we examine the differences between firms that offer more trade credit and firms that offer less trade credit through the lens of the production network. We show that trade credit is an important determinant for the duration of supplier-customer relationships (i.e., network links). Firms offering less trade credit maintain shorter relationships with their customers. This result holds at the macro-level: aggregate trade credit increases the production network's density.

2.3.1 Network characteristics

We check whether high and low R/S firms differ in terms of key network-based characteristics. Prior papers have established that network (eigenvalue) centrality (Ahern, 2013), upstreamness (Gofman et al., 2020), customer concentration and volatility (Herskovic et al., 2020) are associated with risk premia. In addition, we also consider another network-related characteristic that is overlooked by existing network papers:

[15]While a growing concern in the asset-pricing literature pertains to the increasing number of priced factors, the evidence from the GMM analysis is not intended to expand the "factor zoo" (Feng, Giglio, and Xiu, 2020). We examine the relation between the counterparty factor and extant factors in Section OA.3 of the Online Appendix.

the average duration (in months) of a suppliers' links with its existing customers.[16]

Table 4 reports the results of this analysis. The table shows that network centrality cannot explain the counterparty premium, as the R/S-sorted portfolios are indistinguishable in terms of this characteristics. High R/S firms are typically more upstream producers than low R/S firms. However, this cannot explain the counterparty premium as Gofman et al. (2020) show that more upstream firms earn higher returns. In contrast, Table 1 documents that high R/S firms earn lower risk premia.[17] Table 4 also shows that there are no differences between the low and high R/S portfolios in terms of either the concentration or the idiosyncratic volatility of firms' customer bases.[18]

The network-related characteristics in Table 4 indicate a salient difference between high and low R/S firms in terms of link duration. High R/S firms maintain their supplier-customer relationships for about one year longer than low R/S firms. This is economically sizable, given than the median link duration is about three years. We examine the implications of this difference for the structure of the production networks and for the counterparty premium in the next subsections.

2.3.2 Link duration and trade credit

In this section we empirically explore the economic importance of trade credit provision for the expected duration of supplier-customer links. Our main finding is that trade credit positively forecasts the duration of existing supplier-customer links. Consequently, more aggregate trade credit increases the density of the production network.

Firm-level analysis. We estimate Fama-MacBeth regressions that utilize supplier-level characteristics (including R/S) to predict (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

[16]The construction of each of these network-related characteristics is described in Section OA.1 of the Online Appendix. The upstreamness measure employed in this paper is based on the methodology of Antràs, Chor, Fally, and Hillberry (2012), adopted by Gofman et al. (2020).

[17]Nonetheless, in light of this significant difference in upstreamness we perform a conditional double sort procedure in Table 12 of the Online Appendix. The counterparty premium is significant within upstreamness-sorted portfolios. The magnitude of the counterparty premium shows no monotonic pattern in relation to upstreamness. We discuss these results in Section OA.2.

[18]Section 5.3 considers the customer-related characteristics of the R/S-sorted portfolios. We find no difference in the credit ratings of the customers underlying the low and high R/S portfolios. We also find the customers of low R/S firms have lower productivity. We incorporate this feature into our model in Section 3.

beginning in 2003, we 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. We use two measures for $D_{s,t}$. The first measure is the average life of a supplier's existing links going forward (in months). The second measure is an indicator variable that identifies the event in which the links between the supplier and its current customers breaks in the future. Specifically, the indicator takes on a value of one if 50% of the supplier's links that exist in year t do not survive until year $t+3$. The choice of $t+3$ is motivated by the fact that the average duration of supplier-customer links is about three to four years (see Table 4). The supplier-level characteristics, denoted by $\mathbf{X_{s,t}}$, used to predictor $D_{s,t}$ include the R/S ratio, the natural logarithm of the supplier's market value, investment rate, and profitability. Thus, the cross-sectional regressions is

$$D_{s,t} = \boldsymbol{\beta X'_{s,t}} + \varepsilon_{s,t} \quad \forall t \in \{2003, \ldots, 2016\}. \tag{4}$$

Estimating equation (4) on a year-by-year basis eliminates time fixed effects, and allows for a time-varying elasticity of future link duration to R/S. We then compute the time-series average of the estimated slope coefficient, $\hat{\boldsymbol{\beta}}$, across all years, and report the average slope coefficients in Table 5. The table considers both the case in which R/S is the only predictor of $D_{s,t}$, as well as the case in which additional supplier-level characteristics are also included in $\boldsymbol{X_{s,t}}$. Each predictor is scaled by its unconditional standard deviation for ease of interpretation.

The results in Panel A of Table 5 indicate that increases in the intensity of trade credit usage are associated with longer lived supplier-customer relationship. A one standard deviation increase in R/S extends the expected link duration by about 5 months. This effect is statistically significant at the 1% level. R/S remains an economically important predictor of link duration even when additional supplier-level characteristics are included in the regressions. For example, when the profitability, investment rate, and market capitalization of each supplier are also included as predictors, the standardized slope coefficient on R/S remains the largest.

Panel B of Table 5 yields similar results, showing that increases in R/S reduce the probability of supplier-customer links breaking. R/S is the most economically important and statistically significant predictor of the link-break probability. A one standard deviation increase in a supplier's R/S reduces the likelihood of links breaking by 9%. In contrast, a one-standard deviation in a supplier's profitability only reduces the same likelihood by 3%. The effects of a supplier's size and investment on the link-break probability are insignificant.

Production network analysis. The aggregation of equation (4) across all firms implies that the average level of trade credit should positively predict the density of the production network, since more existing relationships will remain alive in the future. Higher density, in turn, can raise diversification, and affect the magnitude of macro fluctuations (see, e.g., Herskovic et al. (2020)).

To test this conjecture we project the future density of the production network on the average level of R/S across all firms:

$$Density_{t+k} = const + \beta_{rs}\overline{R/S}_t + \beta_{IP}\Delta IP_t + \beta_d Density_t + \eta_t, \tag{5}$$

where $Density_t$ is the density of the production network at quarter t, defined as the number of links in the network over the possible number of links in the network,[19] ΔIP_t is the quarterly log-growth rate of industrial production, and $\overline{R/S}_t$ is the simple average of the receivables-to-sales across all firms at the same point in time. The results are reported in Table 6. Each independent variable is normalized by its standard deviation and, for ease of interpretation, we divide each slope coefficient by the unconditional mean of network density.

Consistent with the above conjecture, a one standard deviation increase in aggregate R/S predicts the one-quarter ahead network density will rise by about 4% relative to density's mean. The predictive power of the aggregate R/S ratio is economically sizable and statistically significant up to six-quarters ahead. Furthermore, the economic significance of trade credit is of the same magnitude as that of lagged density.

2.4 Reconciling facts 1 and 2: the link duration premium

Our empirical results have shown that low R/S firms have: higher expected return (Fact 1, Section 2.2); and lower expected duration links with their customers (Fact 2, Section 2.3). In this section, we reconcile these two facts together. We show that differences in link duration can explain the counterparty premium by establishing a novel "link duration" premium.

[19] In a directed network of N firms, the number of possible links is given by $N(N-1)/2$. The results of projection 5 are unchanged if we change the number of possible links to $N^2 - N$ (unrestricted).

To see if dispersion in link duration could drive the R/S spread, it is first necessary to show that link-duration differences create dispersion in risk premia. Hence, we conduct a univariate portfolio sort using the link duration characteristic. We implement this portfolio sort using the same portfolio formation procedure described in Section 2.2.1, with two exceptions. First, the sorts begin in April 2003 instead of June 1978, given the availability of FactSet data. Second, we rebalance the portfolios monthly instead of annually to offset losses in statistical power from the shorter sample period. The results are presented in Panel A of Table 7.

Panel A shows that there is an economically large, statistically significant, and new spread associated with the average life of supplier-customer links. Suppliers that maintain shorter-lived links with their customers earn average value-weighted (equal-weighted) returns that are 0.98% (0.57%) per month higher than those earned by suppliers that maintain longer-lived links. This link duration premium is aligned with the R/S spread, as low R/S firms maintain low duration links. This suggests that the economic origin of the counterparty premium is potentially related to the lifespan of supplier-customer links.

We examine this possibility in Panel B of Table 7 by conducting a conditional portfolio double sort analysis. The first stage of the procedure controls for each supplier's link duration, while the second stage of the procedure constructs the R/S spread *within* each duration-sorted portfolio. Panel B shows that the counterparty premium is jointly equal to zero across the three duration-sorted portfolios. The R/S spread is close to 1% per month among low link duration suppliers, but is insignificant at the 10% level. The R/S spread is qualitatively negative within the medium link duration portfolio, and is statistically indistinguishable from zero among high link duration suppliers. These results show the link duration effect crowds out the counterparty premium.

In sum, our empirical analysis documents a novel relation between trade credit, production network dynamics, and risk premia. Trade credit correlates with the structure of the production network (i.e., the persistence of its linkages), which in turn, correlates with valuations and the marginal utility. Specifically, lower trade credit predicts shorter-lived links between suppliers and customers, which is associated with a higher risk premium. In the next section, we provide a quantitative explanation for the risks incurred with maintaining short-duration links, and the hedging effect of trade credit.

3 Model

This section outlines a discrete-time model with infinite horizons that embeds trade credit into a production framework. The goal of the model is to jointly and quantitatively explain facts 1 and 2 from Sections 2.2 and 2.3, repsectively.

The model features a continuum of supplier firms, each of which offers trade credit to its counterparty – a customer firm. The quality of customer firms is heterogeneous, with a better customer increasing the revenue produced by its supplier. The customer firm is subject to idiosyncratic liquidity shocks and may default. This default probability can be reduced by the supplier firm extending more trade credit, which acts as insurance against the liquidity shock. We present the details below.

3.1 Production, technology, and investment

Consider a supplier firm i whose output (Y_{it}) in period t follows

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

where K_{it} is the level of physical capital, α denotes capital's share of output, A_t is the level of aggregate productivity, and C_{it} is an idiosyncratic component that captures the quality of the current customer of firm i. We discuss the assumption that each supplier has one representative customer in Section 5.2.2. Note that we depart from the standard literature by assuming C_{it} is partially determined by the productivity of a firm's current customer (counterparty). C_{it} can be thought of as the productivity of the supplier-customer pair. There is ample evidence of productivity spillovers or synergies created during the production process. We provide empirical evidence along these lines in Section 5.3. Alternatively, the output of the supplier can be treated as a distinct input good used by the customer, and therefore not perfectly substitutable. In this case, C_{it} may represent markup that the supplier charges the customer for selling a specialized product.

The logarithm of the aggregate productivity process follows a random walk

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

with drift μ_a, volatility σ_a, and where ε^a_{t+1} is an i.i.d. standard normal shock. In contrast, the evolution of C_{it} depends on whether the customer experiences a liquidity shock at the beginning of the next period, as we describe in the next subsection.

The supplier incurs a fixed operating cost in production, ξK_{it}, 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 capital depreciation rate. By increasing the capital stock by I_{it} units, the firm also incurs a capital adjustment cost of $K_{it}\phi\left(I_{it}, K_{it}\right)$, where

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

3.2 Counterparty and trade credit

A high-quality counterparty – captured by a high value of C_{it} – helps increase the output produced by the supplier, Y_{it}. However, counterparties may experience liquidity shocks and default (become insolvent) for various reasons. These liquidity shocks cause the supplier-customer relationship to terminate. We discuss the assumption that supplier-customer links are terminated via liquidity shocks, and refine the interpretation of customer defaults, in Section 5.2.3. Motivated by the empirical evidence, we assume that firm i's current customer is subject to a liquidity shock (and fails) at the beginning of the next period (at time $t+1$) with probability

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

where $\left\{\bar{p}, \underline{p}\right\}$ are the maximum and minimum default probabilities, respectively. $r_{i,t+1}$ represents the amount of trade credit extended by firm i to its customer in period t, to be repaid in period $t+1$ if default does not occur. Choosing $r_{i,t+1}$ is at the discretion of firm i, and takes the form of accounts receivable due in period $t+1$ scaled by the total amount of sales in period t (i.e., R/S). By construction, $r_{i,t+1} \in [0,1]$. By offering more trade credit, firm i provides more liquidity to its customer, and reduces the probability that its counterparty defaults,[20] similar to Cunat (2006). λ is a convexity parameter that determines the rate at which the default probability drops with $r_{i,t+1}$. Note that

[20]Note that $\Gamma_r\left(r_{i,t+1}\right) = -\lambda\left(\bar{p} - \underline{p}\right)\left(1 - r_{i,t+1}\right)^{\lambda-1} < 0$.

the function $\Gamma(\cdot)$ does not depend on aggregate productivity (A_t), making liquidity shocks idiosyncratic. We discuss, and relax, this assumption in Section 5.2.4.

If the current customer of firm i does not experience a liquidity shock at the beginning of period $t+1$, which happens with probability $1-\Gamma\left(r_{i,t+1}\right)$, the current customer repays its supplier the previously extended trade credit, $r_{i,t+1}Y_{i,t}$, and the link between the supplier-customer pair persists to the next period. This implies that

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

If the current customer defaults, with probability $\Gamma\left(r_{i,t+1}\right)$, then 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 for and match with a new customer, firm i needs to pay a predetermined cost of $f_t A_t$ at the beginning of the next period (when matching occurs). Note that for the purpose of stationarity, 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 ε_{t+1}^f is orthogonal to productivity shocks (ε_{t+1}^a). 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. This shock, which represents systematic counterparty risk in our model, captures fluctuations in the cost of finding counterparties and establishing collaborations. These costs include fluctuations in firm entry and regulatory costs. We provide further interpretations for this cost in Section 5.1.

3.3 Firm's problem

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

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

Here, γ_f is the magnitude of the market price of risk of counterparty shocks, ε^f_{t+1}, and SGN is the sign of this shock's price of risk. $\gamma_{a,t}$ is the market price of risk of aggregate productivity shocks, ε^a_{t+1}, which is positive with a time-varying quantity of

$$\gamma_{a,t} = \exp\left(\gamma_a \Delta a_t\right), \tag{15}$$

where $\Delta a_t = \log(A_t/A_{t-1})$. When $\gamma_a < 0$, the price of risk for aggregate productivity shocks varies countercylically. The precise mechanism underlying this well-documented countercyclical variation can, for example, be time-varying risk aversion (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 $\frac{1}{\beta} - 1$.

Below, $\hat{D}_{it}$ is the immediate sales proceeds net of 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 the firm needs to pay an extra cost of $f_t A_t$ in the next period to draw a new counterparty. Therefore, the dividends (D_{it}) paid to shareholders during period t are case dependent. If the customer 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 $t-1$ and

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

We define $V\left(K_{it}, C_{it}, A_t, f_t, R_{it-1}, \iota_{it}\right)$ as the cum-dividend market value of firm i, 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 accounts receivable policies to maximize its market value

$$\begin{aligned} V\left(K_{it}, C_{it}, A_t, f_{t-1}, R_{it-1}, \iota_{it}\right) = \max_{r_{it+1}, K_{it+1}} \quad & \left(1 - \iota_{it}\right) R_{it-1} - \iota_{it} f_{t-1} A_{t-1} + \hat{D}_{it} \\ & + \Gamma\left(r_{it+1}\right) \mathbb{E}_t\left[M_{t,t+1} V\left(K_{it+1}, C_{it+1}, A_{t+1}, f_t, R_{it}, \iota_{it+1} = 1\right)\right] \\ & + \left(1 - \Gamma\left(r_{it+1}\right)\right) \mathbb{E}_t\left[M_{t,t+1} V\left(K_{it+1}, C_{it}, A_{t+1}, f_t, R_{it}, \iota_{it+1} = 0\right)\right]. \end{aligned}$$

Section OA.7 of the Online Appendix describes how to detrended the model, and the procedures to solve the model via value function iteration.

4 Model results

4.1 Calibration

Table 8 shows the calibration of the model parameters in the benchmark case. We discuss the moments targeted by our calibration in Section 4.1.1, and show the fit of the model to the data for aggregate and firm-level quantities in Section 4.1.2.

4.1.1 Parameter choice

Technology. We set the drift, μ_a, and volatility, 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 serves as the idiosyncratic volatility of output in the model. We set this parameter to 0.6 to target the firm-level volatility of sales growth, which is about 30% per annum. Because receivables in the model hedge firms from having to pay rematching costs, the parameters governing the matching cost are tightly linked to moments of firm-level R/S. 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%) per annum.

Capital. We set the depreciation rate (δ) to 0.08, and the capital share of output (α) to 0.4, as is standard in the literature and consistent with the data. The quadratic capital adjustment cost b is set to 0.9 to target the 13% per annum volatility of firm-level investment rates in the data. The fixed cost ξ creates a wedge between a firm's sales and operating income, yielding operating leverage. Thus, we set ξ to 2 to closely match the model-implied volatility of operating profits-to-sales ratio to the data.

Liquidity shock probability. The parameters governing the liquidity shock, $\overline{p}, \underline{p}$, and λ, determine the model-implied duration and distribution of supplier-customer links. Empirically, we find the average life of supplier-customer links of low, medium, and high R/S firms is 3.30, 3.89 and 3.99 years, respectively (recall Table 4). We set these three parameters to target the cross-sectional properties of link duration in a model-implied portfolio sort exercise. Specifically, while $\underline{p}$ ($\overline{p}$) is tightly related to the longest (shortest) model-implied link duration, the convexity parameter λ is related to medium link duration.

SDF. We set the time discount rate β to target a constant risk free rate of 2.1% per annum. There are two market price of risk parameters: γ_a and γ_f. We set these parameters such that the mean (volatility) of the model-implied equity premium is 7.7% (15%) per annum, as in the data. Here, γ_a mainly impacts the volatility of risk premia, as it induces time-varying prices of risk, while γ_f mainly impacts the level of risk premia. The sign of the market price of risk of counterparty shocks (SGN) is negative, consistent with the empirical evidence in Table 3. Importantly, no model parameters target the average returns of the R/S-sorted portfolios.

4.1.2 Model fit for aggregate and firm-level moments

Panel A of Table 9 shows the magnitude of aggregate moments in the model and the data. The growth rate of aggregate output, and the mean and volatility of the equity premium, are successfully targeted by the calibration. The model-implied volatility of aggregate output is just above 2% per annum, and smaller than the data. We deliberately set this volatility to a conservative value such that the model-implied volatility of aggregate consumption (dividends) aligns with the data. The model-implied Sharpe ratio is 0.50 in both the model and the data. While not directly targeted, the autocorrelation of aggregate output in the model is 0.3, and close to its empirical counterpart of 0.22.

Panel B of Table 9 shows both model-implied and empirical moments for firm-level quantities. The firm-level mean of R/S is 23% (20%) per annum in the data (model), while the firm-level volatility of R/S is about 9% (10%) per annum in the data (model). Although both of these moments are targeted by the calibration, the model also closely matches the firm-level autocorrelation of R/S without explicitly targeting this moment with a specific parameter. The model-implied volatility of firm-level investment is 14%, which matches the data, but the autocorrelation of investment rate is somewhat higher in the model than the data. The firm-level volatilities of sales growth and the ratio of operating profits-to-sales are both consistent with the data. The former is 30.2% (33.8%) in the model (data), while the latter is 13% (11.1%) in the model (data).

4.2 Facts 1 and 2: model versus data

We simulate the model for 5,000 firms and 10,000 periods (years). Using this simulated panel, we sort firms into portfolios based on R/S using the same empirical procedure described in Section 2. The low (high) portfolio include firms in the bottom (top) decile of the cross-sectional distribution of R/S as of the formation period.

Our empirical analysis yields two main facts: High R/S firms (1) have considerably *lower* risk premia, and (2) maintain *longer* duration links with their customers. Panel C of Table 9 shows both of these facts are replicated by the model.

The model implied return spread between low and high R/S firms is about 7.1% per annum in the data versus 4.7% in the model. While the model-implied R/S spread is somewhat lower than its point estimate in the data, the model-implied spread is within the spread's empirical confidence interval.

Importantly, all firms in the model are assumed to be suppliers that operate within a given layer of the production network (that is, all suppliers have the same distance to consumers). As a result, the counterparty premium implied by the model can be interpreted as the R/S spread *within* each layer of the production network (i.e., the premium after controlling for suppliers' positions in supply chains), averaged across all production layers. In Section 5.2.1 we show that the counterparty premium exists *within* both downstream and upstream production layers, with an average magnitude of 5.4% per annum, in line with the quantitative model.

Moreover, the expected duration of supplier-customer links for low (high) R/S firms is 3.03 (3.88) years in the model. This is very close to the empirical estimate of 3.30 (3.99) years. Below, we provide the intuition behind the differences in link duration and expected return for the low and high R/S firms in the model.

4.3 The mechanism

The left panel of Figure 1 shows the model-implied policy for a supplier extending trade credit as a function of its customer's quality. The relation between R/S and customer quality is positive and monotonic. The higher the quality of the customer, the greater the supplier's incentive to keep the same customer going forward. This incentive implies that the hedge that suppliers provide their customers in the form of R/S should increase with the customer's quality.

The right panel of the figure shows that higher quality customers endogenously face lower probabilities of default. This is a direct result of the trade credit provision policy. Overall, suppliers that are matched with better quality customers provide more insurance to their customers through R/S. This suggests that these customers are less likely to default, resulting in higher expected link duration.

In contrast, suppliers do not extend any trade credit to a customer if its quality is sufficiently low. This is because the supplier actually hopes a liquidity shock will cause its current customer to default, allowing the firm to draw a new customer from the pool. This policy is optimal for the supplier because reversion to the mean suggests that the expected quality of a new customer will exceed the low quality of the current customer. The monotonic relation between R/S and customer quality suggests that R/S can proxy for the underlying (unobserved) quality of the customer.

To explain the sign of the counterparty premium in the model, we describe how each of the priced shocks, ε^f and ε^a, contributes to the spread.

Contribution of $\boldsymbol{\varepsilon^f}$ shocks. Because firms with low R/S provide only a small hedge to their customers, these customers have a higher default probability. Thus, low R/S firms are more likely to search for a new customer next period. While all firms are negatively affected by shocks that increase the rematching cost f, low R/S firms are more adversely affected by these shocks, as they are more likely to pay the cost associated with rematching. Collectively, this implies $\beta_f^{R/S=LOW} < \beta_f^{R/S=HIGH} < 0$, where $\beta_f^j = \frac{1}{\sigma_f} \frac{\partial V_{j,t+1}}{\partial \varepsilon_{t+1}^f}$.

Contribution of $\boldsymbol{\varepsilon^a}$ shocks. 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 those of high R/S firm (recall the production function in equation (6)). Since the fixed cost ξ does not scale proportionately with sales (or alternatively, with the customer's quality and/or aggregate productivity), the fixed cost creates operating leverage. With lower sales, the degree of operating leverage is higher for low R/S firms. That is, changes in aggregate productivity have a larger percent change on the profitability of low R/S firms than 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 $0 < \beta_a^{R/S=HIGH} < \beta_a^{R/S=LOW}$, where $\beta_a^j = \frac{1}{\sigma_a} \frac{\partial V_{j,t+1}}{\partial \varepsilon_{t+1}^a}$.

Overall premium. Combining the effects of the priced shocks described above, the spread between low and high R/S firms, or the counterparty premium, is

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

Since the price of risk of productivity shocks is positive ($\gamma_{a,t} > 0$), while the price of risk of counterparty shocks is negative ($\gamma_f < 0$) in both the model and the data, both shocks contribute positively to the spread, and the counterparty premium is positive.

While the counterparty premium is *qualitatively* positive in the model, the *quantitative* success of the model is not obvious. First, none of the model parameters targets cross-sectional return moments, but the model is still able to match the empirical premium, which is sizable. This illustrates the plausibility of our risk-based explanation for the counterparty premium. Second, the relative contributions of ε^f and ε^a shocks to the spread depend on the model's parametrization. We show below that in our empirical calibration, the counterparty shock explains most of the variation in the counterparty spread. Thus, a model with only a single aggregate productivity shock will be unable to explain the empirical facts. Third, in Section 5.2.4 we introduce systematic customer defaults to the model. This is a countervailing force that can induce a negative counterparty premium. We demonstrate that the model's quantitative success in explaining the counterparty premium is barely diminished under this extension.

Relative contribution of $\boldsymbol{\varepsilon^f}$ shocks. Almost the entire R/S spread is driven by the counterparty shocks (ε^f). We show this by reporting how perturbing key model parameters impacts our quantitative results. Column (3) of Table 10 shows that if the market price of risk of counterparty shocks, γ_f, is zero, then the spread is still positive but small in magnitude. The fact that the spread falls sharply suggests that almost 98% of the counterparty premium in the model is explained by the counterparty factor.

Additionally, Column (4) of the table shows that when the sign of the market price of risk of the counterparty shocks is switched to positive ($SGN = 1$), the counterparty premium turns negative. Clearly, the first term in equation (19) dominates the premium, once again confirming that of the spread is driven by the ε^f shocks.

5 Discussion and Robustness

We provide a discussion of the model's assumptions, implications, and robustness. Section 5.1 discusses several connections of the counterparty factor to macroeconomic fundamentals. In Section 5.2 we discuss several modeling assumptions, and demonstrate that the link between the model and the data is sufficiently tight. In section 5.3 we empirically evaluate key model predictions and implications.

5.1 Counterparty risk factor and the macroeconomy

Counterparty risk takes the form of a cost that a supplier firm has to pay to search for and be matched with a new counterparty (customer). This cost aims to capture, in a reduced form, systematic frictions involved in finding a customer. Motivated by the empirical evidence in Section 2.2.3, shocks to this cost have a negative price of risk in the SDF. In this section, we offer several interpretations for this search cost. We explain how these costs can arise in general equilibrium, and why the underlying forces that increase the matching cost also increase the representative agent's marginal utility (i.e., why the shocks have a negative price of risk).

Drop in new entrants. The frictions involved in the search for a new counterparty can rise when the pool of potential customers shrinks. With fewer customers looking for a supplier, it takes longer for a supplier to find a counterparty, resulting in a more costly search process. In practice, there are many reasons why the pool of potential customers may shrink. This includes, for example, a drop in the number of newly created firms that are natrually searching for a supplier. At the same time, a drop in the number of new establishments is likely to induce a negative price of risk since new entrants represent young firms with many growth opportunities. A drop in the cohort of new firms can significantly and persistently reduce the aggregate productivity, and therefore lower the growth of the economy (e.g., Clementi and Palazzo (2016) discuss how firms' entry amplifies macroeconomic shocks). This leads to a drop in welfare, and to a negative market price of counterparty risk.[21]

According to the narrative above, the counterparty premium should increase as the number of new entrants falls. We provide empirical support for this prediction in two

[21] This negative price of risk depends on the effect of search costs on future consumption growth. A drop in expected consumption growth can increase marginal utility under recursive preferences.

steps. First, we isolate the premium component of the R/S spread via the projection

$$Spread_{t+1} = \gamma_0 + \gamma_1' \Gamma_t + \varepsilon_{t+1}, \tag{20}$$

where $Spread_{t+1}$ is the spread between low and high R/S firms at time $t+1$, and Γ_t is a vector of time-t measurable predictors. This vector includes the lagged value of the R/S spread, the market return, the market price-dividend ratio, the corporate default spread, and the term spread. The conditional counterparty premium at time t, denoted $Prem_t$, is defined as the expected value of $Spread_{t+1}$, or the fitted value of the projection above, $\hat{\gamma}_0 + \hat{\gamma}_1 \Gamma_t$. All variables in equation (20) are aggregated to quarterly frequency to match the frequency of firm entry and exit data from the Bureau of Labor Statistics (BLS). In the second step, we regress the conditional premium on the contemporaneous difference between the rates of establishment deaths and births from the BLS. To be consistent with the two-factor structure of the model, we also control for the aggregate TFP. The second-step projection is

$$Prem_t = \rho_0 + \rho_{DMB} \left(DeathMinusBirth\right)_t + \rho_{TFP} TFP_t + \varepsilon_t, \tag{21}$$

where $DeathMinusBirth_t$ is the quarterly rate of establishment deaths minus the rate of establishment births, and TFP_t is total factor productivity. TFP_t is measured using the utilization-adjusted productivity from Fernald (2012).[22] All variables in equation (21) are standardized so that the slope coefficients can be interpreted as (partial) correlations. The results are reported in columns (1) and (2) of Table 11.

The results show that when the death minus birth rate increases, the pool of firms looking for a potential supplier shrinks, which should result in a higher counterparty premium. Consistently, the first column of Table 11 shows that the correlation between the counterparty premium and the death minus birth rate is almost 50%. Column (2) shows that this conclusion remains materially unchanged even after controlling for aggregate productivity. The slope coefficient on TFP is negative and close to zero. This is in line with the fact that the counterparty premium in the model is countercyclical, yet the contribution of aggregate TFP to the premium is quantitatively small.

Rising competition of suppliers. 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 of supplier firms. Lower market power among

[22] We thank the Federal Reserve Bank of San Fransisco for making this data available.

suppliers can be triggered by a lower degree of substitutability between products, lower barriers to entry, or higher spillovers of knowledge. Another example for a drop in suppliers' relative market power can be attributed to the departure of key talent. As shown by Dou et al. (2019), key talent creates a more loyal customer base. Greater labor mobility can therefore decrease the relative bargaining power of suppliers. For all these reasons, when suppliers have lower market power, a potential customer has, in relative terms, more bargaining power. The customer can squeeze more rents from the supplier firm, leading to a higher rematching cost.

Meanwhile, an increase in supplier-level competition can lead to larger displacement risk. As shown by prior studies (e.g., Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, and Stoffman, 2020), displacement can lead to a negative price of risk.

We estimate the following projection to examine the plausibility of these narratives

$$Prem_t = \rho_0 + \rho_{COMP} \left(RelativeCompetition\right)_t + \rho_{TFP} TFP_t + \varepsilon_t, \tag{22}$$

where $Prem_t$ is the counterparty premium from equation (20), TFP_t is the same productivity measure underlying equation (21), and $RelativeCompetition_t$ measures the competitiveness of suppliers relative to customers. To measure relative competitiveness, we follow three steps. First, in each quarter we partition our sample of firms based on the bottom and the top 30^{th} percentiles of the BEA-implied upstreamness measure from Gofman et al. (2020). While the former group (bottom 30%) represents downstream firms (i.e., relative customers), the latter group (top 30%) represents upstream firms (i.e., relative suppliers). Next, we compute the Herfindahl–Hirschman index (HHI) associated with the group of firms classified as customers and suppliers separately. Finally, we subtract the HHI of suppliers from the HHI of customers. When the difference in HHI between customers and suppliers increases, customers have a higher degree of concentration relative to suppliers. Alternatively, the degree of competition among suppliers increases relative to customers. This is a situation in which the cost of a supplier matching with a customer is likely to be higher, as suppliers have less bargaining power. Thus, the counterparty spread is anticipated to rise. We report the results of estimating equation (22) in columns (3) and (4) of Table 11. Once again, all variables are standardized so that slope coefficients represent (partial) correlations.

Column (3) of Table 11 shows that an increase in the market power of customers relative to the market power of suppliers is associated with an increase in the counterparty premium. The correlation is 0.30 and statistically significant at the 1% level. Column (4) shows that the correlation between the counterparty premium and the concentration of customers relative to suppliers remains positive and significant after controlling for aggregate productivity.

In column (5), we combine equations (21) and (22) and estimate a projection that includes the death minus birth rate of establishments, the difference in HHI between customers and suppliers, and TFP. The slope coefficients on both the death minus birth rate and the difference in HHI are positive and significant. Thus, the interpretations that larger search costs are associated with a drop in the mass of newly created firms or a decrease in the degree of market competition among suppliers do not crowd each other out. The effect of TFP remains close to zero, consistent with the low marginal quantitative contribution of productivity shocks to the R/S spread in our model.

In Section OA.3 of the Online Appendix we consider three other macroeconomic interpretation for the counterparty factor (search costs): changes in regulation, deadweight costs, and *non-linear* relation to extant macroeconomic factors (i.e., aggregate investment). The model in Section 3 refrains from explicitly endogenizing the search friction, both for simplicity, and because these friction can stem from many sources at once, as suggested by the discussion above. We leave the exercise of modeling a general equilibrium that incorporates all or some of the above frictions to future research.

5.2 Discussion about the model's assumptions

5.2.1 Suppliers' perspective (within production-layer spread)

The real economy features suppliers and customers that are organized in a complex production network. However, in the interest of tractability,[23] our model focuses on the stock returns of suppliers with low versus high R/S only. This is equivalent to assuming that all firms in the model operate within the same layer of the production network. That is, each firm in the model is assumed to have the same distance

[23]Solving a quantitative model with both suppliers and customers fully specified is not feasible for two reasons. First, solving an endogenous network formation model is a NP-hard (non-deterministic polynomial-time hardness) problem that is impractical given our cross-section features 5,000 firms. Second, the input factors in our setup are not merely flow variables, but rather stock variables (receivables, capital). As a result, a full-scale numerical model would necessitate a high-order Krusell-Smith procedure, which can be highly inaccurate in the presence of network granularity.

from final consumers in the supply chain, or a fixed upstreamness. Thus, the model-implied counterparty premium can be interpreted as the average R/S spread within each production layer.

To ensure that our model is tightly linked to the data, Table 12 shows the magnitude of the counterparty premium within each layer of the production network. We estimate these magnitudes using a double-sort analysis. We first sort firms into portfolios based on their upstreamness measure, as in Antràs et al., 2012 and Gofman et al., 2020. Then, within each upstreamness-sorted portfolio, we sort firms on the basis of R/S. The table shows that the counterparty premium is positive and statistically significant within each upstreamness-sorted portfolio (i.e., in each layer of the production network). The average R/S spread across the upstreamness-sorted portfolios is 0.45% per month, or approximately 5.4% per annum. This is very close to the model-implied counterparty premium.

5.2.2 Number of customers

Our model assumes that each supplier is matched with only one customer, while in the data, a supplier can have multiple customers. There are two reasons for this modeling choice. First, Table 4 shows that there is no difference in the customer concentration between low and high R/S firms. Consequently, it does not seem that customer diversification plays a pivotal role in explaining the results. Moreover, Table OA.6.10 in the Online Appendix shows that there is no risk premium spread between suppliers that have few versus many customers. Because heterogeneity in the number of customers does not impact firms' risk premia, we abstract from this type of heterogeneity in the model.

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

5.2.3 Termination of supplier-customer links

Our model assumes that supplier-customer relationships terminate upon a customer default. Customer defaults serve as a mechanism to break the link between the two firms, as guided by theoretical and empirical research in corporate finance that highlights the role of trade credit for providing liquidity insurance to customers (e.g., (Cunat, 2006; Wilner, 2000)). Nonetheless, there are two important caveats in interpreting this termination mechanism. First, default in our setup is not equivalent to strict "exit" events (as can happen following a failure to repay corporate bonds). Rather, default can be interpreted as a delay in repayment which disrupts the credit line that a supplier provides to its customer. Similarly, the default event can capture any exogenous reason which makes the customer strategically leave its supplier (e.g., a supply chain disruption in which the customer switches to a new suppliers).[24]

Second, we consider a model extension in which the supplier can strategically terminate the relationship with its customer. Specifically, we provide suppliers with the option to sever the link with its current customer. Upon termination, the supplier pays the rematching cost f_t, and draws a new customer next period with quality $C_{i,t+1}$ drawn from equation (12). Moreover, if the supplier chooses to strategically end the relationship, it does not extend any trade credit. We find that the counterparty premium increases in this setup increase by about 0.5% compared to the benchmark case (i.e, the premium is close to 5% p.a.). The intuition is straightforward. Assume that the supplier cannot strategically terminate the relationship with its customer. If the supplier is matched with a poor quality customer, it opts to extend no trade credit (i.e., the suppler has low R/S), and hopes that its customer will default next period (see Figure 1). In this case, suppliers that are matched with low quality customers are more likely to pay the rematching cost f_t, but the likelihood of payment is less than one. On the other hand, if the supplier is matched with a poor quality customer, and can strategically bail, it has to pay the rematching cost f_t with probability one. Thus, strategic defaults by suppliers only increase the exposure of low R/S firms to customer

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

search frictions, and amplify the counterparty premium.

5.2.4 Systematic defaults

Because the correlation between doubtful receivables and market returns is empirically small (about 10%), the baseline model assumes that customer defaults are idiosyncratic. While liquidity shocks in the data mostly affect customers idiosyncratically, it is conceivable that the probability of default on trade credit may increase for all customers in states of low aggregate productivity. To account for this possibility, we change equation (10) to

$$\Gamma\left(r_{i,t+1}\right) = \exp(\Delta a_t)^{\nu}\left(\bar{p} - \underline{p}\right)\left(1 - r_{i,t+1}\right)^{\lambda} + \underline{p}. \tag{23}$$

Here, the probability of default for all customers is inversely related to both the R/S ratio, $r_{i,t+1}$, and the log-growth rate of aggregate productivity, Δa_t, provided $\nu < 0$. We set ν to -0.5, which implies that in the worst (lowest) state of Δa_t the probability of default increases by about 2%. This magnitude is considerable given the mean ratio of doubtful receivables-to-sales, a proxy for defaulted trade credit, is 1% in the data.

Even with a liquidity probability function that allows for systematic defaults under a "worst-case scenario" for ν, the low (high) R/S portfolio earns 12.42% (8.58%) per annum. This means that the model-implied counterparty premium slightly drops to 3.84%, or by about 0.9% compared to the benchmark case. Considering the large magnitude of ν, this is an *upper bound* on how much systematic defaults can reduce the spread. Importantly, since the lower bound of the empirical R/S spread's 95% confidence interval is 2.39% per annum, the model-implied counterparty premium with systematic defaults still falls inside the empirical confidence interval.

Equation (23) suggests that firms with high R/S have more to lose in bad states, making them more sensitive to systematic defaults, and increasing their exposures to ε^a shocks. While this attenuates the spread, this force does not quantitatively dominate the lower exposure (in absolute value) of high R/S firms to ε^f shocks.

5.3 Testing the model's restrictions and implications

Our model makes a few assumptions and provides several testable implications: (a) The model assumes that a supplier's productivity is positively correlated with its customer's productivity (see equation (6)). (b) In the model, suppliers endogenously choose to extend more trade credit to higher quality customers (see Figure 1). Thus, our model predicts a positive correlation between a supplier's trade credit provision and its customer's productivity. (c) We have assumed that customers mainly differ in their productivities but not so much in the probability of default (credit risk). (d) From the lens of the model, firms with lower account payables should have slightly greater risk premia. This is because firms that endogenously receive less trade credit from their suppliers are lower quality (lower C) customers. These customer firms also have higher operating leverage (assuming similar technology and adjustment cost functions). As suggested by Novy-Marx (2011), they could have higher expected returns.

To test points (a), (b), and (c) 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 is used to identify the set of active supplier-customer relationships. Next, we estimate a cross-sectional regression in each June from 2003 to 2016:

$$y_{c,t} = \alpha + \rho_t x_{s,t} + \varepsilon_{c,t}, \quad \forall t \in \{2003, \ldots, 2016\}. \tag{24}$$

Each supplier-customer link is treated as a distinct observation. Additionally, each of the firm-level characteristics in the regression is standardized by its 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 $\{\hat{\rho}_t\}_{t=\{2003,\ldots,2016\}}$ obtained by estimating equation (24) 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 in by equation (6), the correlation between customer- and supplier-productivity is positive, and significant at the 5% level.

Panel B of the table computes the correlation between supplier-level R/S and customer-level TFP. The results show this correlation is positive and 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.

Panel C of the table computes the correlation between supplier-level R/S and an indicator variable taking the value one if the customer has an investment grade credit rating. The results show that this correlation is close to zero, and insignificant. This supports our modeling choice that better quality customers differ in their productivity, but not necessarily in their ex-ante default probability.[25]

To test point (d), in Table OA.6.12 of the Online Appendix we sort firms into portfolios based on the ratio of account payables to the cost of goods sold. We find that firms with proportionally lower accounts payable have higher expected returns compared to high payable firms, but the magnitude of the spread is small and amounts to about 0.12% per month. This is qualitatively consistent with prediction (d).

6 Ruling out alternative mechanisms

Our model suggests that the main explanation for the counterparty premium is that high R/S firms are hedged against systematic frictions involved in the search for new customers. While we do not claim that this is the only mechanism that can rationalize the R/S spread, our model demonstrates that this mechanism is quantitatively important. In Table 14, we offer a comprehensive examination of the characteristics of R/S-sorted portfolios. The table helps to rule out some alternative mechanisms that may also generate a spread between low and high R/S firms.

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, asset growth, or idiosyncratic return volatility.[26] We use other characteristics reported in Table 14 to rule out plausible and alternative explanations for the counterparty premium below.

Trade credit as a precautionary savings mechanism. Firms may choose to sell more goods for credit to reduce the cyclicality of their earnings. Assume that a

[25]Table OA.6.13 in the Online Appendix also shows that the customers of low and high R/S firms pay similar loan spreads for private debt, have similar proportions of secured debt outstanding, and are equally likely to have financial covenants included in their debts. This further supports the notion that customers do not differ in terms of their ex-ante default probabilities.

[26]Relatedly, Table 4 shows that there are also no statistically significant differences between the extreme portfolios for most network-related characteristics. Upstreamness cannot explain the counterparty premium because high R/S firms are more upstream, but Gofman et al. (2020) show that upstream firms have higher expected returns. Moreover, Table 12 shows that the counterparty premium is positive among both downstream and upstream firms.

firm is experiencing high sales today, but anticipates a drop in future sales (e.g., due to an expected deterioration in aggregate economic conditions). If the firm sells its goods today for cash only, then its revenue will be very volatile: high today and low in the future. However, if the firm sells some of its goods for credit, it will receive more cash in future (bad) states by collecting the trade credit. The cash obtained from the trade credit can either be used for payouts, to smooth the cyclicality of dividends, or as a buffer against future bad shocks, such as avoiding costly external financing.

In contrast to this hypothesis, we do not find evidence that lower trade credit is driven by such a precautionary savings motive. First, Table 14 shows that low R/S firms do not hold extra cash, as there is no difference in the cash holdings of low and high R/S firms. Second, we find that firms with higher R/S today do not have lower future sales. The cumulative sales growth from the beginning of the portfolio formation period to the end of the holding period is larger for high R/S firms, although the difference is not significant. This suggests that the incentive of high R/S firms to engage in smoothing is small. Third, firms may also smooth their profits by holding higher inventories. Belo and Lin (2012) and Jones and Tuzel (2013) show that higher inventory growth firms have lower expected returns. However, we find no significant different in inventory growth rates between the R/S-sorted portfolios. This is another indication that differences R/S are not primarily driven by smoothing incentives.

Differential lending capacity. A high R/S ratio may indicate a firm with a better underlying ability to extend trade credit. For instance, firms that have lower financial constraints may not only earn higher stock returns (e.g., Lamont, Polk, and Saaá-Requejo (2001)) but may also be able to extend more trade credit. In contrast to this logic, Table 14 shows that there is no difference between low and high R/S firms in terms of the Hadlock and Pierce (2010) measure of financial constraints.[27] Moreover, low R/S firms have lower leverage. The table also shows no differences between low and high R/S firms in terms of their costs of private loans, the likelihood of borrowing on a secured basis, or the propensity for their debt to include covenants.[28] This not only eliminates leverage as a potential explanation for the spread, but also suggests

[27]Relatedly, Table OA.6.11 in the Online Appendix shows that financial distress cannot explain the counterparty premium either. That is, after controlling for the Ohlson (1980) measure of distress, we still document a quantitatively large and statistically significant counterparty premium.

[28]We thank Michael Roberts for making the Chava and Roberts (2008) DealScan-Compustat Linking Database available.

that net of liabilities, low R/S firms may actually posses a larger lending capacity.

Investment-trade credit tradeoff. If firms choose to extend less trade credit when they are endowed with more growth opportunities, then these firms may have to give up on some investment opportunities if they provide too much trade credit and do not have enough internal funds available. If the trade-off between investment projects and receivables is binding, low R/S firms should be riskier and also exhibit lower asset growth rates. Opposite to this rationale, there is no statistical difference in asset growth between the extreme R/S-sorted portfolios. In addition, while Ai and Kiku (2016) associate idiosyncratic volatility with the existence of growth options, there is no significant difference between the extreme portfolios in this measure.[29]

Independence from related spreads. Table 14 raises the possibility that the counterparty premium may be related to the profitability premium or momentum. This is because low (high) R/S firms tend to be relatively profitable (unprofitable) firms with high (low) stock return momentum. Each of these potentially confounding effects, related to profitability and momentum, is well-established in the context of the asset-pricing literature.[30] In Section OA.4 of the Online Appendix we demonstrate that the counterparty premium is distinct from the profitability premium and the momentum effect. The R/S spread remains significant after controlling for these characteristics via a double-sort procedures and Fama-Macbeth regressions. Using a similar methodology, in Section OA.5 of the Online Appendix we show that the accruals (working capital) effect cannot explain the R/S spread. However, conditioning on trade credit, the working capital spread is no longer significant.

Ex-ante industry-level differences. Since different industries have different business models and levels of competition, firms in some industries may rely on trade credit more heavily than others. As a result, sorting firms on the basis of R/S may capture ex-ante heterogeneity in industry affiliation. To show this is not the case, we perform a conditional double sort analysis. We first sort firms into industries based on the Fama-French 10 industry classification. We then sort firms within each industry

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

[30]For instance, Fama and French (2006) and Hou et al. (2015) demonstrate that more profitable firms typically earn higher returns. Similarly, Jegadeesh and Titman (1993) find that low (high) momentum firms earn low (high) future returns.

into three portfolios based on R/S in an identical fashion to the benchmark analysis. Table OA.6.9 in the Online Appendix shows the results. The R/S spread is positive within all but two industries. The spread is also significant in most of the industries considered. The null hypothesis that the R/S spread is zero across all industries is rejected with a p-value of less than 1%. The simple average of the industry-level R/S spread is 0.58% per month, which is 97% of the magnitude of the unconditional R/S spread reported in Table 1. Thus, by and large, the counterparty premium is driven by differences *within* industries and not across industries.

Trade credit factoring. The anomalous relation between trade credit and risk premia, as well as the explanation that we offer for this relation in our study, is not confounded by that fact that some firms may sell their trade credit to a third party. First, the ability to factor trade credit may reduce the riskiness of high R/S firms (by decreasing their exposure to their customers' shocks). Relatedly, Costello (2019) shows that using collateral can also mitigate suppliers' concerns for the customer's credit risk. However, if the underlying source of risk behind the counterparty premium was a pure 'default' risk, and if selling trade credit potentially eliminates this risk, then this would result in a (close to) zero spread between high and low R/S firms.[31] Factoring does not explain why high R/S firms earn a *lower* risk premium. Second, once trade credit is extended, the customer's liquidity is improved regardless of whether the supplier sells the trade credit to a third party. In case of a customer default, the supplier may not suffer a loss if trade credit is factored, but it must still engage in a search for a new customer. These inevitable search frictions render low R/S firms riskier.

Bargaining and market power. Trade credit could be determined via Nash bargaining between suppliers and customer. If a supplier (customer) has less (more) vertical bargaining power, then the equilibrium R/S would be higher. However, there are two indications that a bargaining story is unlikely to explain the empirical findings. First, Table 4 shows that low and high R/S firms do not differ in terms of (eigenvalue) centrality, a common measure of suppliers' market power. Likewise, customer concentration is also associated with bargaining power, but the same table shows no difference in the HHI of customers associated with low and high R/S suppliers. That is, the cus-

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

tomers of high R/S firms are not more concentrated.

Importantly, differences in bargaining power may be driven by *unobservables*. For quantitative reasons, we deliberately opt to focus on a theoretical explanation that depends on an observable (link duration). Second, a market-power based narrative implies that high R/S firms ought to have low bargaining power. Low vertical bargaining power could imply that the firm has a lower operating margins, increasing the firm's exposure to systematic shocks (e.g., Dobson, 2004; Novy-Marx, 2011), and implying that high R/S firms should be riskier.[32] Lastly, while *firm-level* heterogeneity in market power does not seem to provide an empirically supported explanation for the counterparty premium, *systematic* fluctuations in the market power of suppliers have a strong connection to the counterparty risk factor, as shown in Table 11.

7 Conclusion

We examine the relation between trade credit, supplier-customer link duration, and risk. 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 counterparty risk premium. The counterparty premium is unexplained by common asset-pricing factors and accounting characteristics, such as value, investment, and working capital. An asset-pricing factor based on the counterparty premium is priced negatively in stock returns. Second, 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. Third, 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.

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 of heterogeneous quality. The customer may experience a liquidity shock and

[32]In Bustamante (2019), low vertical bargaining power firms are safer because they absorb less of the future supply chain shocks. Thus, the relation between bargaining power and risk premia is, at the very least, ambiguous.

default on its outstanding debt. Suppliers can extend trade credit to provide liquidity to their 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 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 counterparty. We discuss possible interpretation for these systematic shocks. Higher systematic rematching cost are associated with a smaller pool of potential customers, induced by a smaller cohort of new firms, an increase in competition among suppliers, an increase in regulation and contracting standards, and the deadweight costs of default. An interesting direction for future research is to model some of the mechanisms above in a general equilibrium setup, and endogenize the price of risk of counterparty shocks. Another avenue for future studies is to examine more broadly the connection between credit lines and link duration in the context of financial networks involving banks and other financial institutions.

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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 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	1.185	5.029	1.191	6.348
Medium	1.062	4.545	1.286	6.122
High R/S	0.589	5.981	0.744	7.476
Spread	0.597	4.128	0.448	3.439
(L-H)	(2.95)		(2.28)	

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), while MOM is the momentum factor of Carhart (1997). In column 4 (5), Profit. and Invest. correspond to the RMW and CMA factors (ROE and I/A factors) of the Fama and French (2015) five-factor (Hou et al. (2015) q-factor) model. Parentheses report Newey and West (1987) robust t-statistics. Returns span July 1978 to December 2016.

	(1)	(2)	(3)	(4)	(5)
MKTRF	-0.312	-0.308	-0.288	-0.256	-0.276
	(-6.13)	(-6.03)	(-5.45)	(-5.02)	(-5.08)
SMB		0.035	0.025	0.132	0.154
		(0.47)	(0.34)	(1.64)	(2.35)
HML		0.053	0.096	-0.050	
		(0.56)	(1.09)	(-0.51)	
MOM			0.107		
			(1.84)		
Profit.				0.367	0.322
				(3.40)	(2.88)
Invest.				0.138	0.181
				(1.06)	(1.55)
α	0.798	0.775	0.684	0.585	0.487
	(4.07)	(3.97)	(3.57)	(3.06)	(2.56)

Table 3: The market price of 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 counterparty risk factor. Here, the counterparty risk factor is constructed by buying firms with high R/S ratios and selling firms with low R/S ratios. All firms underlying each R/S portfolio are value weighted. Each model is estimated by generalized methods of moments (GMM) using the moment conditions $\mathbb{E}\left[M_t r^e_{i,t}\right] = 0$, where $r^e_{i,t}$ represents the excess return of test asset i at time t and M_t denotes the stochastic discount factor. We assume that M_t is specified as $M_t = 1 - \boldsymbol{b}'\boldsymbol{f}_t - b_{CPR}CPR_t$, where $\boldsymbol{f}_t$ represents the common factors associated with either the CAPM or the Fama and French (1993) three-factor model and CPR_t represents the counterparty risk factor. Each of these factors is demeaned, and $(\boldsymbol{b}'\ b_{CPR})'$ denotes the column vector of the risk factor loadings on the SDF that are estimated. The estimation of each asset-pricing model is conducted using the value-weighted returns of the following three sets of test assets: (1) 25 size and book-to-market portfolios, (2) the first set of test assets plus the 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	+CPR	CAPM	+CPR	CAPM	+CPR
b_M	3.675	11.587	3.538	5.316	3.431	5.236
$t(b_M)$	(3.15)	(5.34)	(3.07)	(3.85)	(3.07)	(4.36)
b_{CPR}		-25.939		-4.168		-5.816
$t(b_{CPR})$		(-5.06)		(-2.64)		(-3.82)
MAE	0.871	0.619	0.871	0.853	0.879	0.829

Panel B: Four-factor model						
	25 portfolios		42 portfolios		62 portfolios	
	FF3F	+CPR	FF3F	+CPR	FF3F	+CPR
b_M	3.988	9.313	4.042	5.022	3.952	5.481
$t(b_M)$	(3.14)	(4.74)	(3.29)	(3.79)	(3.36)	(4.34)
b_S	1.489	1.190	0.372	0.673	0.181	0.534
$t(b_S)$	(0.87)	(0.61)	(0.22)	(0.40)	(0.11)	(0.32)
b_H	6.375	4.777	4.991	4.992	4.385	4.138
$t(b_H)$	(3.62)	(2.18)	(2.85)	(2.75)	(2.52)	(2.36)
b_{CPR}		-17.803		-3.589		-5.331
$t(b_{CPR})$		(-4.08)		(-2.27)		(-3.52)
MAE	0.608	0.478	0.728	0.708	0.775	0.737

Table 4: 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	0.42	-0.11	(-0.91)
Upstreamness	1.65	2.74	3.03	-1.38	(-15.34)
HHI (Customer)	0.17	0.35	0.24	-0.07	(-1.03)
IVOL (Customer)	1.47	1.49	1.24	0.24	(1.15)
Duration	39.60	46.69	47.98	-8.38	(-2.68)

Table 5: 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). The regression specification is presented in equation (4), and the procedure we follow to estimate these regressions is described in Section 2.3.2. Our measure of link duration is either (1) the average future duration of each supplier's links with its customers (measured in months in the left panel), or (2) an indicator variable that identifies the situation in which the supplier-customer link breaks (in the right panel). The event that Break = 1 in the right panel corresponds to the situation in which at least half or more of a supplier's customers at time t are no longer the supplier's customers in three years time. Finally, Newey and West (1987) robust t-statistic are reported in parentheses, and each supplier-level characteristic is standardized by dividing the characteristic by its unconditional standard deviation. The time period for the analysis ranges from June 2003 to June 2016.

	Future duration		Pr (Break = 1)	
Constant	55.62	56.70	0.58	0.57
	(11.49)	(11.38)	(23.32)	(25.76)
R/S	4.69	5.86	-0.09	-0.09
	(3.59)	(3.66)	(-3.11)	(-3.98)
SIZE		-2.20		-0.01
		(-5.15)		(-0.34)
I/K		-2.84		0.01
		(-1.94)		(0.88)
ROA		2.82		-0.04
		(3.61)		(-3.36)

Table 6: Predicting the production network's density

The table reports the results of time-series regressions that predict the density of linkages in the production network using the lagged aggregate receivables-to-sales ratio and the lagged density of the production network. Specifically, the projection we estimate is: $Density_{t+k} = const + \beta_{rs}\overline{R/S}_t + \beta_{IP}\Delta IP_t + \beta_d Density_t + \eta_t$, where $Density_{t+k}$ is the density of the network at time $t+k$, IP_t is the quarterly log-growth rate of industrial prodction, and $\overline{R/S}_t$ is the equal-weighted average R/S ratio across all firms at time t. We measure $Density_{t+k}$ as the ratio of observed links in the production network at time $t+k$ divded by the maximum potential number of links at the same point in time. Each independent variable is scaled by its standard deviation, and for ease of interpretation, we divide each slope coefficient by the unconditional mean of the density measure. We consider forecast horizons (k) of one, three, five, and seven quarters ahead. Newey and West (1987) robust t-statistic are reported in parentheses, and the time period for the analysis ranges from January 2004 to December 2016.

	1Q ahead		3Q ahead		5Q ahead		7Q ahead	
$\overline{R/S}$	0.06	0.04	0.05	0.03	0.06	0.05	0.04	0.04
	(3.25)	(4.25)	(2.53)	(2.50)	(2.67)	(2.75)	(1.42)	(1.48)
$Density$		0.07		0.06		0.03		0.01
		(13.82)		(5.29)		(1.98)		(0.34)
IP		0.00		-0.02		-0.01		0.01
		(0.28)		(-1.85)		(-0.53)		(0.37)
R^2	0.17	0.83	0.09	0.51	0.13	0.20	0.03	-0.01

Table 7: Controlling for link duration

The table reports the average monthly portfolio returns obtained from univariate and conditional portfolio double-sort procedures related to the average duration of each supplier's links with its customers, as described in Section 2.4. Panel A conducts univariate portfolio sorts on link duration, and reports portfolio returns on both a value-weighted (left columns of the panel) and equal-weighted (right columns of the panel) basis. Here, Mean (SD) refers to the mean (volatility) of monthly returns. Panel B reports the results of a conditional double-sort procedure in which we construct the R/S spread *within* each of three portfolios that are formed on the basis of each firm's link duration. 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 that the R/S spread across all three duration portfolios is zero. Finally, the sample period is from July 2003 to December 2016.

Panel A: Univariate sorts on link duration					
	Value-weighted			Equal-weighted	
Portfolio	Mean	SD		Mean	SD
Low (L)	2.005	2.005		1.978	6.111
Medium	0.860	3.795		1.141	6.245
High (H)	1.021	1.021		1.406	6.147
Spread	0.984	2.533		0.572	2.881
(L-H)	(4.26)			(2.49)	
Panel B: Controlling for duration					
	Low Dur.	Medium	High Dur.		
Low R/S	2.28	0.82	1.49		
Medium	1.97	0.84	0.98		
High R/S	1.30	0.83	1.02		
Spread	0.98	-0.02	0.47	Joint test	
(L-H)	($p = 0.11$)	($p = 0.52$)	($p = 0.20$)	($p = 0.61$)	

Table 8: Model calibration

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

Symbol	Value	Parameter	Symbol	Value	Parameter
Panel A: Technology			*Panel B: Capital*		
μ_a	2%	Productivity growth rate	δ	8%	Capital depreciation rate
σ_a	2.7%	Productivity shock volatility	α	0.4	Capital share of output
σ_c	0.6	Counterparty quality dispersion	b	0.9	Quadratic adjustment cost
f_0	0.4	Average matching cost	ξ	2	Fixed operating cost
σ_f	0.1	Matching cost volatility			
Panel C: Liquidity shock probability			*Panel D: SDF*		
$\overline{p}$	0.5	Pr(Shock if R/S=0)	β	0.979	Time discount factor
$\underline{p}$	0.25	Pr(Shock if R/S$\rightarrow \infty$)	γ_a	-85	Price of productivity shocks
λ	10	Convexity of shock function	γ_f	7.6	Magnitude of priced counterparty shocks
			SGN	-1	Sign of priced counterparty shocks

Table 9: 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 model-implied moments are based on model simulated data for 7,000 periods (years) and 5,000 firms. The first 2,000 periods of the simulation are discarded to remove the dependence on the initial state. The moodel-implied sorting procedure is identical to the empirical strategy described in Section 2. Low (high) R/S firms refers to the firms in the bottom (top) 10% of the cross-sectional distribution of the receivables-to- sales ratio.

Statistic	Data	Model	Statistic	Data	Model
Panel A: Aggregate moments			Panel B: Firm-level moments		
Output growth:			*Receivables-to-sales (R/S):*		
Mean	2.57	2.01	Mean	23.15	20.14
Volatility	4.17	2.23	Volatility	9.33	10.18
Autocorrelation	0.22	0.33	Autocorrelation	0.49	0.45
Equity premium:			*Investment-to-capital (I/K):*		
Mean	7.37	7.80	Volatility	13.40	14.29
Volatility	15.46	15.66	Autocorrelation	0.48	0.19
Sharpe ratio	0.50	0.50	*Other:*		
			Sales growth volatility	30.25	33.82
			Operating profits / sales volatility	13.60	11.13
Panel C: R/S portfolio returns			Panel D: R/S portfolio duration		
Low R/S	14.22	13.30	Low R/S	3.30	3.03
Medium R/S	12.74	10.38	Medium R/S	3.89	3.82
High R/S	7.07	8.53	High R/S	3.99	3.88
R/S spread	7.16	4.77	High R/S	3.99	3.88

Table 10: Counterparty premium: sensitivity analysis and extensions

The table shows model-implied average returns of the 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 the matching shocks in column (3), or a positive price of risk (with the same absolute value as the benchmark calibration) for the matching shocks in column (4).

	(1)	(2)	(3)	(4)
Moment	Data	Model	$\gamma_f = 0$	$SGN = 1$
Mean return low R/S	14.22	13.30	5.106	4.268
Mean return mid R/S	12.74	10.38	5.045	4.380
Mean return high R/S	7.07	8.53	5.002	4.420
R/S spread	7.16	4.77	0.104	-0.152

Table 11: Economic interpretations of the counterparty premium

The table reports the results of the projection: $Prem_t = \rho_0 + \rho_{DMB}\left(DeathMinusBirth\right)_t + \rho_{COMP}\text{RelativeCompetition}_t + \rho_{TFP}TFP_t + \varepsilon_t$, where $Prem_t$ is the time-t expected value of the return spread between low and high R/S firms at time $t+1$, $DeathMinusBirth$ is the difference between death and birth rate of establishments from BLS, $\text{RelativeeCompetition}_t$ is concentration of customers relative to suppliers, and TFP_t is the utilization-adjusted total factor productivity from Fernald (2012). $\text{RelativeCompetition}_t$ is constructed in three steps. First, in each quarter, each firm in the sample is denoted a customer (supplier) firm if its BEA-implied upstreamness score from Gofman et al. (2020) is below (above) the 30^{th} (70^{th}) percentile of upstreamness for that period. Next, the Herfindahl–Hirschman index (HHI) of the group of customers and suppliers is computed. Finally, the HHI of the supplier firms is subtracted from the HHI of the customer firms. In all regressions both the dependent and independent variables are standardized, and Newey and West (1987) t-statistics are reported in parentheses. The sample is quarterly from 1992-Q3 to 2016-Q4.

	(1)	(2)	(3)	(4)	(5)
Deaths minus births	0.48	0.46			0.41
	(2.31)	(2.64)			(2.18)
RelativeCompetition			0.30	0.31	0.22
			(3.35)	(3.48)	(2.31)
TFP		-0.19		-0.26	-0.21
		(-1.30)		(-1.29)	(-1.48)
$\bar{R}^2$	0.22	0.25	0.08	0.14	0.29

Table 12: 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	High Upstreamness	
Low R/S	1.14	1.17	0.93	
Medium	1.14	1.09	1.01	
High R/S	0.85	0.55	0.49	
Spread	0.29	0.62	0.44	Joint test
(L-H)	($p = 0.08$)	($p = 0.01$)	($p = 0.03$)	($p = 0.03$)

Table 13: Evaluating the model's 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. In Panel C, an indicator taking the value of one if the customer is investment grade 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.

	Prediction (a)	Prediction (b)	Prediction (c)
	$\rho\,(TFP_c, TFP_s) > 0$	$\rho\,(TFP_c, R/S_s) > 0$	$\rho\,(\mathbb{I}_{\text{Invest. grade customer}}, R/S_s)$
ρ	0.036	0.164	-0.001
	(2.884)	(10.496)	(0.296)

Table 14: 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	0.14	0.50	-0.48	
ln(Size)	8.50	8.98	8.52	-0.02	(-0.14)
B/M	0.42	0.51	0.59	-0.07	(-1.57)
Cash / Assets	0.11	0.13	0.11	-0.01	(-0.81)
Leverage	0.23	0.21	0.34	-0.10	(-9.55)
Hadlock-Pierce	-3.91	-4.07	-4.00	0.08	(1.29)
Asset growth	0.16	0.13	0.14	0.01	(0.59)
IVOL	1.47	1.32	1.51	-0.04	(-0.43)
Cum. future sales growth	0.32	0.23	0.42	-0.09	(-1.37)
Inventory growth	0.15	0.12	0.17	-0.02	(-0.46)
ROA	0.07	0.08	0.03	0.05	(7.59)
Momentum	0.23	0.21	0.18	0.02	(2.09)
Loan Spread	0.84	0.86	1.04	-0.20	(-1.35)
Secured Debt	0.11	0.14	0.22	-0.11	(-1.60)
Debt Covenants	0.23	0.24	0.22	-0.01	(-0.71)

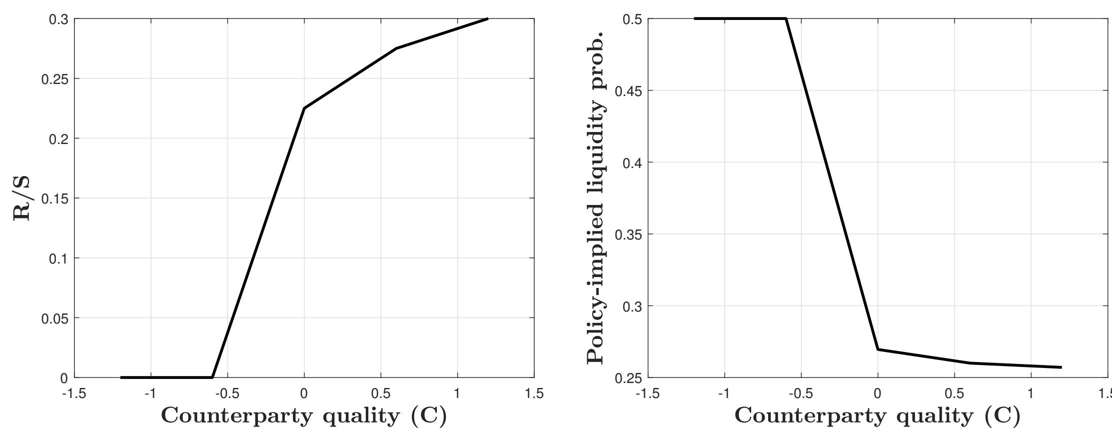

Figure 1: Model-implied policy functions

The left figure shows the model-implied policy for a firm's (supplier's) R/S (r) against different values of counterparty (customer) quality (C). The right figure shows the liquidity probability ($\Gamma(r)$ from equation (10)) 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 $t-1$.

Cash-to-assets. The cash-to-assets ratio computed as the value of cash and cash equivalents (Compustat Annual item CHE) divided by total assets (Compustat Annual item AT).

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

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

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

Debt covenants (Customer). We compute the proportion of debt covenants included in private debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2016, we identify the set of customers associated with each supplier. Debt covenants is an indicator variable equal to one if a loan includes a financial covenant, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Finally, we compute the average debt covenant indicator across all of the customers associated with a given supplier.

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

Hadlock-Pierce index of financial constraints. Following Hadlock and Pierce

(2010), the Hadlock-Pierce index of financial constraints (SA) is based on the size and age of each firm in the Compustat universe. The size of each firm is measured as the natural logarithm of the real value of book assets, expressed in terms of 2009 dollars. The real value of book assets is capped at $4.5 billion, meaning that firms with more than $4.5 billion worth of real total assets have their value of real total assets set to $4.5 billion. Age is measured the number of years the firm has been listed in Compustat with a non-missing stock price, and is capped at 37 years. Finally, the SA index of financial constraints for firm i in fiscal year t is $SA_{i,t} = -0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.040 \times \text{Age}_{i,t}$.

HHI (Customers). We compute the Herfindahl–Hirschman Index (HHI) index of the set of customers associated with each supplier using the FactSet Revere database. Specifically, in each month between April 2003 and December 2016, we record the customers associated with each supplier. Then, using the total sales of each customer, we compute the sale HHI of its customes.

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

IVOL (Customer). We compute the idiosyncratic return volatility of each supplier's customers using the FactSet Revere database. Specifically, in each month between April 2003 and December 2016, we identify the set of customers associated with each supplier. Next, for each customer, we compute its idiosyncratic return volatility (IVOL) in accordance with Ang et al. (2006) (see above). Finally, we compute the sales-weighted average IVOL across all the customers associated with the supplier.

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

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

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

Loan spread (Customer). We compute the loan spread of all the private debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2016, we identify the set of customers associated with each supplier. oan spread is calculated as the total annual spread on a given loan over LIBOR, net of upfront fees, expressed as a percentage. If a firm has more than one loan outstanding at a given point in time, the variable is averaged across the firm's loans. Finally, we compute the average loan spread across all of the customers associated with a given supplier.

Momentum. A firm's past return momentum in month t is defined as its cumulative return between months $t-11$ and $t-1$ Jegadeesh and Titman (1993). This measure is constructed using CRSP Monthly return data that is adjusted for de-listing events.

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

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

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

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

Secured debt (Customer). We compute the proportion of secured debts issued by the customers of each supplier using the FactSet Revere and DealScan databases. Specifically, in each month between April 2003 and December 2016, we identify the set of customers associated with each supplier. Secured debt is an indicator variable equal to one if a loan is secured by collateral, and zero otherwise. If a firm has more than one loan outstanding at a given point in time, the indicator is averaged across the firm's loans. Finally, we compute the average secured debt indicator across all of the customers associated with a given supplier.

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

Upstreamness. 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. (2020).

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

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

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

OA.2 The counterparty premium within production layers

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

To ensure that our model is tightly linked to the data, Table 12 shows the magnitude of the counterparty premium within each layer of the production network. We estimate these magnitudes using a double-sort analysis. We first sort firms into portfolios based on their upstreamness measure, as in Antràs et al., 2012 and Gofman et al., 2020. Then, within each upstreamness-sorted portfolio, we sort firms on the basis of R/S. The table shows that the counterparty premium is positive and statistically significant within each upstreamness-sorted portfolio (i.e., in each layer of the production network). The average R/S spread across the upstreamness-sorted portfolios is 0.45% per month, or approximately 5.4% per annum. This is very close to the model-implied counterparty premium.

OA.3 Counterparty risk factor and the macroeconomy (supplementary)

We offer several additional interpretations for the search costs featured in the model section, to supplement the evidence provided in Section 5.1.

Regulation. 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 incurred 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 (e.g., Herskovic, 2018).

Deadweight costs. Since a supplier pays the matching cost exactly when its current customer experiences a liquidity shock, this coincides with states of the world in which the customer defaults on its trade credit. Thus, the cost can also reflect a deadweight loss of default, or the loss of potential interest payments from the customer to its supplier. This reduces the profits of the supplier that flow its owners (consumers), thereby leading to a reduction in welfare and a negative price of risk.

Non-linear relation to extant factors. In Section 2.2.3 we show that the counterparty risk factor has a negative price of risk controlling for the market, profitability, and investment factors. In our analysis we consider a linear pricing kernel with constant risk exposures (i.e., an unconditional model). Deviations from these standard assumptions could reflect a non-linear relation between the counterparty premium and extant empirical asset-pricing factors. Such relations are not ruled out by the previous discussion. For instance, a change in the mass of new entrants, which affects the search costs of customers, can reflect a non-linear function of the investment factor. To see this, assume there is a fixed cost for entering the market. If growth opportunities for firms are only modest, aggregate investment by incumbent firms may rise, but the benefit of exploiting these growth options may not justify the costs for potential entrants. If growth opportunities are abundant, aggregate investment rises sharply, and potential entrants may find it optimal to enter the market to share in these growth options. Thus, entry is a non-linear function of aggregate investment activity. Non-linear relations of this sort are captured in a reduced-form manner through the shocks to ε^f.[33]

[33] To illustrate this, in column (5) of Table 2 we show that projecting the counterparty premium on the q factors of Hou et al. (2015) q produces an unconditional alpha of 0.50% per month with a t-statistic of 2.55. Untabulated results show that when we augment the independent variables with the squared and cubic powers of the investment factor, the alpha associated with the counterparty premium drops to 0.31% per month with a t-statistic of 1.41.

OA.4 Independence from profitability and momentum

We demonstrate that the counterparty premium is distinct from the profitability premium and the momentum effect. Table OA.6.4 reports the value-weighted returns from a conditional double-sort procedure in which the first stage sorting variable in Panel A (Panel B) is ROA (momentum), 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, but also remains statistically significant at the 1% level or better. Furthermore, the joint test on the null hypothesis that the R/S spread is zero across the three profitability-sorted portfolios is rejected at the 1% level.

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

Table OA.6.5 confirms the above results using Fama-Macbeth regressions. We demonstrate that when projecting future excess returns on R/S and a host of other firm-level characteristics known to predict returns (including ROA and momentum), the slope coefficient on R/S remains negative and significant.

OA.5 The counterparty premium versus the accruals effect

Sloan (1996) shows that firms with low accruals (i.e., less working capital) earn high future returns. This pattern in returns is attributed to investors overestimating the persistence of accruals when forecasting future accounting earnings. However, since trade credit is a component of current assets (and hence accruals), there is a mechanical positive relation between accruals and R/S. In this section we empirically examine whether the counterparty premium survives controlling for accruals. We also explore the opposite relation, and examine whether R/S explains the accruals effect.

Following Sloan (1996), the total accruals (denoted ACC) of firm i and time t are

$$\mathrm{ACC}_{i,t} = \frac{(\Delta\mathrm{ACT}_{i,t} - \Delta\mathrm{CHE}_{i,t}) - (\Delta\mathrm{LCT}_{i,t} - \Delta\mathrm{DLTT}_{i,t} - \Delta\mathrm{TXP}_{i,t}) - \mathrm{DP}_{i,t}}{0.5 \times (\mathrm{AT}_{i,t} + \mathrm{AT}_{i,t-1})}, \quad (25)$$

where 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), R/S and accruals are positively correlated by construction. Consistently, we find empirically that firms with low R/S also have lower accruals. However, the difference in accruals between low and high R/S firms is small. The magnitude of the difference is 0.01, with a t-statistic of 1.92.

In light of the (low) correlation, we first show that the R/S spread survives controlling for accruals. To show this, we implement a double sort analysis, and construct the R/S spread within three accruals-sorted portfolios. The results are reported in Panel A of Table OA.6.6 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 significant at the 1% and 10% level, respectively. Furthermore, a joint test shows that the counterparty premium is significant at the 5% level across all accruals portfolios. Collectively, this evidence suggests that the accruals (working capital) effect cannot explain the R/S spread.

In Panel B of Table OA.6.6 we reverse the order of the sorts to examine whether the accruals effect survives controlling for R/S. The results show that the accruals spread is statistically significant only within the portfolio of medium R/S firms. Moreover, the null hypothesis that the accruals spread is zero across all three R/S-sorted portfolios is not rejected. Since conditioning portfolios on trade receivables drives out the accruals effect, while the converse does not hold, the economic determinants of the counterparty premium may also shed light on the accruals effect of Sloan (1996).

Related, Wang (2019) constructs a cash-conversion-cycle (CCC) measure that, similar to accruals, combines multiple operating ratios and accounting variables (including accounts receivable) to establish a return spread that is interpreted as mispricing. In contrast, we focus on the pricing implications of the receivables component only, and use novel network data in the next section to show that there is a risk-based explanation for the R/S spread. Consistent with this difference, Table OA.6.7 in shows that the CCC spread is insignificant during out sample period when we sort portfolios annually instead of monthly, as in Wang (2019). Additionally, we show that the R/S spreads survives controlling for CCC. In Table OA.6.8 we construct the R/S spread within three CCC-sorted portfolios. The counterparty premium is jointly significant across the three CCC-sorted portfolio, with a p-value of 0.03.

OA.6 Supplemental tables

Table OA.6.1: 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 2.2.1, 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	1.410	5.330	0.988	4.750
Medium	1.356	4.440	0.804	4.629
High R/S	0.701	6.180	0.490	5.810
Spread	0.708	4.168	0.499	4.100
(L-H)	(2.22)		(1.96)	

Table OA.6.2: Portfolios sorted on R/S: alternative breakpoints
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 2.2.1, 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.

	Mean	SD
Low R/S	1.129	4.292
Medium	1.050	4.571
High R/S	0.871	5.451
Spread	0.259	2.498
(L-H)	(2.09)	

Table OA.6.3: Transition matrix of constituents between R/S portfolios

The table shows the probability that a firm sorted into portfolio $i \in \{\text{Low, Medium, High}\}$ in year t, where i is the row index, is sorted into portfolio $j \in \{\text{Low, Medium, High}\}$ in year $t+1$, where j is the column index. The construction of the R/S-sorted portfolios is identical to the benchmark analysis described in Section 2.2.1. The sample spans from July 1978 to December 2016.

Portfolio in	Portfolio in year $t+1$		
year t	Low	Medium	High
Low	0.849	0.129	0.022
Medium	0.015	0.948	0.037
High	0.018	0.372	0.610

Table OA.6.4: Controlling for profitability and momentum: double-sort analysis
The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) in Panel A (Panel B) is a firm's ROA (momentum), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the control variable using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the control variable in the fiscal year ending in calendar year $t-1$. Second, within each characteristic-sorted portfolio, we further sort firms into three additional portfolios on the basis of R/S using the 10^{th} and 90^{th} percentiles of R/S from the fiscal year ending in calendar year $t-1$. This process produces nine portfolios that are each held from the beginning for July in year t to the end of June in year $t+1$, at which point in time all portfolios are rebalanced. The last two rows of each panel show the R/S spread along with its associated p-value in parentheses. These p-values are computed using Newey and West (1987) robust standard errors. The table also reports the p-value from a joint test on the null hypothesis that the R/S spread across all three characteristic-sorted portfolios is zero. The sample period is from July 1978 to December 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 momentum				
	Low MOM	Medium	High MOM	
Low R/S	1.28	1.16	1.52	
Medium	0.86	1.06	1.26	
High R/S	-0.08	0.68	0.68	
Spread	1.36	0.48	0.84	Joint test
(L-H)	($p=0.00$)	($p=0.01$)	($p=0.01$)	($p=0.00$)

Table OA.6.5: Fama-MacBeth regressions

The table reports the results of Fama-MacBeth regression that project future annual firm-level excess returns on each firm's current R/S ratio while controlling for various firm-level characteristics that are known to predict returns. Here, each variable is standardized by its unconditional standard deviation. The table reports the slope coefficient associated with each predictor, as well as the Newey and West (1987) robust t-statistic associated with each point estimate. The sample period is from July 1978 to December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R/S	-1.83	-1.88	-1.61	-1.61	-1.50	-1.44	-1.11
	(-2.62)	(-2.62)	(-2.51)	(-2.45)	(-2.26)	(-2.37)	(-1.97)
ln(ME)		-3.39					-3.27
		(-2.36)					(-2.69)
B/M			3.47				1.62
			(4.31)				(2.85)
MOM				-0.96			-0.49
				(-0.88)			(-0.51)
ROA					1.11		1.97
					(0.91)		(1.85)
I/K						-2.75	-2.24
						(-3.81)	(-3.71)
R^2	0.005	0.015	0.016	0.011	0.016	0.013	0.039

Table OA.6.6: 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 OA.6.7: Annual sort on cash conversion cycle

The table reports the average monthly value-weighted returns of portfolios sorted on cash conversion cycle (CCC) defined in Wang (2019). The construction of these portfolios is identical to the benchmark analysis as described in Section 2.2.1. That is, portfolios are formed at the end of each June over the sample period. 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.

Portfolio	Mean	SD
Low CCC	0.991	5.804
Medium	1.038	4.519
High CCC	1.027	5.027
Spread	-0.036	3.837
(L-H)	(-0.21)	

Table OA.6.8: Controlling for cash conversion cycle: double-sort analysis

The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first dimension sorting variable) is a firm's cash conversion cycle (CCC), and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of tCCC using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of CCC in the fiscal year ending in calendar year $t-1$. Second, within each CCC-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.

	Low CCC	Medium	High CCC	
Low R/S	1.18	1.20	0.94	
Medium	1.01	1.06	1.01	
High R/S	0.46	0.67	0.94	
Spread	0.72	0.54	0.00	Joint test
(L-H)	($p=0.06$)	($p=0.01$)	($p=0.50$)	($p=0.03$)

Table OA.6.10: Number of customers and stock returns

The table reports the average monthly value- and equal-weighted portfolio returns obtained from univariate sorts on the average number of customers per supplier based on FactSet relationship data. Here, the cross-section of firms is sorted into three portfolios based on the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the number of customers at the end of the previous month. 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. Parentheses report t-statistics computed using Newey and West (1987) robust standard errors. Finally, the sample period is from July 2003 to December 2016.

	Value-weighted		Equal-weighted	
Portfolio	Mean	SD	Mean	SD
Low Num. Cust.	0.946	4.095	1.238	6.183
Medium	0.914	3.741	1.232	6.214
High Num. Cust.	0.864	4.136	1.348	6.308
Spread	0.082	2.154	-0.109	2.439
(L-H)	(0.50)		(-0.64)	

Table OA.6.9: R/S spread within industry portfolios

The table shows the results of a conditional double sort procedure. First, firms are sorted into nine groups based on their industry affiliation. Here, we use the Fama-French 10 industry classification to assign firms to industries, and drop firms assigned to the "Other" industry. Next, within each industry we sort firms into three portfolios based on R/S. Firms are sorted into portfolios at the end of each June following the portfolio formation procedure described in Section 2. The table then reports the mean return associated with each R/S-sorted portfolio, the low-minus-high R/S spread in each industry, and the Newey and West (1987) robust t-statistic associated with each R/S spread. In the final row of the table, the "Joint test" reports the p-value associated with the null hypotheses hat the R/S spread is jointly equal to zero across the nine industries.

Industry	Low R/S	Medium	High R/S	Spread	(L-H)
Nondurable	1.56	1.17	0.99	0.57	(2.44)
Energy	1.54	1.10	0.13	1.41	(3.20)
Telecommunication	1.42	1.01	0.38	1.05	(2.25)
High Tech	1.60	1.09	0.25	1.36	(4.39)
Health	1.50	1.20	0.68	0.82	(2.24)
Shops	1.12	1.22	1.04	0.09	(0.37)
Utilities	1.12	1.01	0.91	0.21	(0.58)
Durable	0.95	1.04	1.10	-0.15	(-0.42)
Manufacturing	0.81	1.07	0.95	-0.14	(-0.60)
				Joint test	($p < 0.01$)

Table OA.6.11: 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-stage sorting variable) is a firm's Ohlson (1980) O-Score, and the second-stage sorting variable is a firm's receivable-to-sales (R/S) ratio. The sorts are conducted as follows. First, at the end of each June, we sort the cross-section of firms into three portfolios on the basis of the O-Score using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the O-Score 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.

	Low O-Score	Medium	High O-Score	
Low R/S	1.18	1.22	0.06	
Medium	1.05	1.12	0.57	
High R/S	0.63	0.62	-0.41	
Spread	0.55	0.60	0.48	Joint test
(L-H)	($p = 0.03$)	($p = 0.00$)	($p = 0.18$)	($p = 0.03$)

Table OA.6.12: Sort on accounts payable to cost of goods sold

The table reports the average monthly value-weighted returns of portfolios sorted on the ratio of account payables to cost of goods solds (AP/COGS), as well as the spread between the low and high AP/COGS portfolios. The construction of these portfolios is identical to the benchmark analysis, described in Section 2.2.1. 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.

Portfolio	Mean	SD
Low AP/COGS	1.105	5.229
Medium	1.041	4.577
High AP/COGS	0.977	5.313
Spread	0.128	3.490
(L-H)	(0.71)	

Table OA.6.13: Characteristics of the customers underlying the R/S portfolios
The table shows the value-weighted characteristics of the customers underlying 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)
Loan spread (Customer)	1.19	2.04	1.67	-0.48	(-1.23)
Secured debt (Customer)	0.34	0.36	0.33	0.01	(0.45)
Debt Covenants (Customer)	0.50	0.59	0.54	-0.04	(-0.09)

OA.7 Model solution

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

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

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

$$\begin{aligned}\tilde{J}\left(\tilde{K}_{it}, C_{it}, A_t/A_{t-1}, f_t\right) = \max_{r_{it+1}, \tilde{K}_{it+1}} \quad & \tilde{Y}_{i,t}(1-r_{it+1}) - \xi\tilde{K}_{it} - \tilde{I}_{it} - \phi\left(\tilde{I}_{it}, \tilde{K}_{it}\right)\tilde{K}_{it} \\ & + \Gamma(r_{it+1})\left(\frac{A_t}{A_{t-1}}\right)\mathbb{E}_t\left[M_{t,t+1}\left(-f_t + \tilde{J}(\tilde{K}_{it+1}, C_{it+1}, A_{t+1}/A_t, f_{t+1})\right)\right] \\ & + \left[1-\Gamma(r_{it+1})\right]\mathbb{E}_t\left[M_{t,t+1}\left(\tilde{Y}_{it} r_{it+1} + \left(\frac{A_t}{A_{t-1}}\right)\tilde{J}(\tilde{K}_{it+1}, C_{it}, A_{t+1}/A_t, f_{t+1})\right)\right] \\ & \text{s.t.} \\ & \tilde{Y}_{i,t} = \left(\frac{A_t}{A_{t-1}} C_{it}\right)^{1-\alpha}\tilde{K}_{it}^{\alpha} \\ & \left(\frac{A_t}{A_{t-1}}\right)\tilde{K}_{it+1} = (1-\delta)\tilde{K}_{it} + \tilde{I}_{it} \\ & \phi\left(\tilde{I}_{it}, \tilde{K}_{it}\right) = b\left(\frac{\tilde{I}_{it}}{\tilde{K}_{it}} - \delta\right)^2 \\ & \frac{A_{t+1}}{A_t} = \exp(\mu_a + \sigma_a \varepsilon^a_{t+1})\end{aligned}$$

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