Counterparty Risk: Implications for Network Linkages and Asset Prices ⋆

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Abstract

We study the relation between trade credit, asset prices, and production-network linkages. Empirically, firms extending more trade credit earn 7.6% p.a. lower risk premiums and maintain longer relationships with customers. Using a production-based model, we quantitatively explain these novel facts. Trade credit reduces the departure probability of high-quality customers, thereby reducing firms' exposures to systematic costs incurred in finding new customers. The mechanism predicts that the aggregate amount of trade credit proxies for customer-search costs and that suppliers with shorter-duration links to customers command higher expected returns. We confirm these and other novel predictions in the data. (*JEL* G12, E32, E23, D25, L14)

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The allocation of credit among economic agents is integral to 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 a 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 firms' *largest* sources of short-term financing, and consequently plays a key macroeconomic role. When selling goods, firms typically demand cash for only a fraction of the sales. The rest is sold for credit and logged as accounts receivable. Yet, the implications of trade credit for production-related risks and asset prices remain unexplored. Does trade credit provision affect a firm's riskiness? How does the aggregate amount of trade credit relate to macro risks? Can trade credit provide information on the quality of a firm's trade counterparties (i.e., customers), or the firm's risk of losing its relationships with them? We address these questions empirically and theoretically.

On the empirical front, we establish two main novel facts. First, we find that trade credit is informative about firms' risk profiles (fact 1). Firms that extend more trade credit, and have higher ratios of receivables-to-sales (henceforth R/S), earn a significantly *lower* risk premium. The return spread between low and high R/S firms, which we name the "counterparty premium," is close to 0.63% per month, or above 7.62% per annum. Second, trade credit is informative about the dynamics of supplier-customer links (fact 2). At the micro-level, high R/S firms maintain longer duration links to their customers. At the macro-level, aggregate trade credit positively predicts the production network's density. Together, these facts demonstrate that trade credit is valuable for understanding both risk premiums and interfirm links in the production network.

On the theoretical front, we construct a production-based asset pricing model to quantitatively explain these facts. Each firm is matched with a customer of heterogeneous quality, but the links between firms and customers can break (i.e., customers may depart). Customer departure is risky for firms as searching for new customers is costly. Trade credit serves as an insurance policy against this risk by providing a mechanism that induces high-quality customers to keep their relations with the firm. By offering more trade credit to a better customer, the firm provides liquidity to this customer or, equivalently, sells its product at a discount because payments are delayed. This raises the likelihood of retaining this customer and increases the duration of the supplier-customer link. Consequently, trade credit hedges firms against the costs involved in the search for new customers that rise in bad states of the world.[1] Thus, firms that offer more R/S are safer.

The sign of the counterparty premium is a priori puzzling given two hypotheses that posit *opposite* relations between trade credit provision and risk. On the one hand, offering trade credit could increase a firm's operating risk, as firms that extend trade credit are more exposed to adverse shocks that affect their counterparties. If the customer is subject to shocks that deteriorate its financial condition, these shocks can then propagate to the supplier through unrepaid trade credit. Moreover, as defaults tend to occur in bad states of the world, these adverse shocks covary with the business cycle. Under this conjecture, high R/S firms are riskier and should command a higher risk premium.

On the other hand, endogenously riskier firms (e.g., those matched with lower-quality customers) may choose to extend less trade credit. While this conjecture predicts higher risk premiums for low R/S firms and is consistent with the data, the source of this risk is not obvious. In particular, we show that the counterparty premium cannot be explained by common asset pricing factors or firm-level characteristics. Double-sort analyses and Fama-MacBeth regressions show that R/S predicts stock returns negatively, even after controlling for a host of characteristics, including profitability, accruals, and distress. We also 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.

What is the economic driver of this new factor? Trade credit provides key information about the production network that sheds light on this question. In particular, low R/S firms maintain lower duration links with their customers. R/S emerges as a powerful predictor of both the survival and the length of supplier-customer relationships. This result holds at the aggregate-level: a one-standard-deviation increase in mean R/S predicts the production network's density will rise by about 6%. These novel findings lead to our risk-based hypothesis. If matching with new customers is costly during bad states, then customer turnover is risky. By extending trade credit, the firm encourages good customers

[1] Throughout this study, we will refer to this risk as "counterparty risk." The term reflects cyclical variation in the costs associated with the search for new customers. While our definition of counterparty risk differs from others, ours is related to the *departure* of a firm's counterparty.

to retain their business, and in turn, reduces its exposure to risks associated with searching for new customers. Consequently, firms providing more trade credit have lower risk premiums (fact 1) and longer duration relations with their customer (fact 2).

We explore a rich set of new empirical predictions in support of this mechanism. The first three predictions establish an empirical proxy for customer-search costs and demonstrate its ability to price the returns of the R/S-sorted portfolios: (a) The total amount of trade credit in the economy increases with macro conditions that make searching for and replacing customers more costly. For instance, if the mass of new firms looking for a supplier shrinks, it becomes more difficult for a supplier firm to find a new customer. Likewise, when competition for customers intensifies, suppliers have lower bargaining power compared to customers, which makes matching with a customer more costly. Both of these variables are highly correlated with the aggregate amount of trade credit; (b) fluctuations in the aggregate amount of trade credit render the pricing error associated with the counterparty premium insignificant, consistent with the notion that this macro time-series proxies for customer-search costs; and (c) both stock returns and cash flows are negatively exposed to innovations in the aggregate trade credit. The market price of risk associated with these innovations is also negative, in line with search costs rising in high marginal utility states.

The last three predictions explore key implications for real economic activity: (d) dividends, productivity, and profit margins are significantly lower for firms that recently matched with new customers, consistent with the assumption of costly search; (e) firms extend more trade credit to better-quality customers that are worth retaining, as proxied for by total factor productivity (TFP) and other productivity ratios; (f) we uncover a novel 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% per month higher than those earned by suppliers that maintain longer duration links. This related spread is also explained by exposures to systematic customer search costs.

We formalize this risk-based hypothesis by constructing a production-based model that quantitatively explains why low R/S firms have higher stock returns, in spite of their lower exposure to customer default risk exposure and their lower duration links with customers (i.e., facts 1 and 2). In the model, each supplier is matched with a customer of heterogeneous quality and each supplier's revenue increases with the quality of its customer. Every period, the customer may experience a shock that terminates its relationship with its supplier. This shock can, for example, capture a customer strategically switching to a different supplier or a liquidity shock that renders the customer insolvent. The two interpretations are materially equivalent. Suppliers can choose to extend trade credit to the current customer, thereby reducing the probability of the interfirm link breaking. Intuitively, trade credit provides liquidity to the customer and partially insures the customer against liquidity shocks. This reduces the likelihood of the customer defaulting and is consistent with a vast literature in corporate finance that stresses the role of trade credit in liquidity provision.

If the customer does not experience a shock that terminates the relationship, then it repays the trade credit, and the link between the two firms persists. Otherwise, the trade credit is lost, consistent with the realization of a liquidity shock. At that point, the supplier has to engage in a costly search for a new customer. Notably, the supplier has to pay a cost that fluctuates systematically to search for and rematch with a new counterparty. Innovations that increase these common search and rematching costs are denoted "counterparty shocks" and are *endogenously* highly correlated with the aggregate amount of trade credit, as in the data.

In the model, the relation between trade credit and risk premium is ex ante ambiguous. On the one hand, if a firm is matched with a higher-quality customer, it has a greater incentive to retain the customer. To do so, the firm provides more insurance to its customer via trade credit, increasing the expected duration of the supplier-customer link. Hence, a high R/S firm is less likely to search for a new customer next period, and is less exposed to counterparty shocks. Put differently, R/S acts as a hedge against the costs involved in the search for new customers that is useful when the current customer is worth retaining. On the other hand, customer defaults are systematically more frequent in times of low productivity. If a firm provides more trade credit, it increases the potential losses incurred in these bad states. Under our empirically disciplined calibration, the former force dominates. The model-implied counterparty premium is about 6% p.a. and falls within the empirical confidence interval for the R/S spread. This quantitative success provides support for our mechanism, as the calibration does not target any cross-sectional return spread.

We conclude with several empirical and theoretical robustness checks. First, we show that other prominent explanations for the counterparty premium do not have strong empirical support, including differences in bargaining power and lending capacity across firms. Moreover, we show that differences in neither trade credit provision across industries nor trade credit factoring (i.e., the collateralization of trade credit) drives the counterparty premium. Second, we consider several model extensions by allowing for the strategic termination of links and differences in firm-level productivity that are unrelated to customer quality. The counterparty premium's magnitude is materially unchanged.

In all, trade credit is a substantial source of financing, and is informative about (1) a firm's risk premium, (2) its expected link-duration with customers, (3) the productivity of its customers, (4) the density of the production network, and (5) systematic changes in the search costs for new customers. Thus, trade credit is an important determinant of firm-level and macro-level risks.

Our paper is most closely 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 premiums. 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., Belo, Lin, and Bazdresch 2014; Favilukis and Lin 2016; Belo et al. 2017) to explain aggregate and cross-sectional risk premiums via differential exposures to aggregate productivity. Our study proposes an alternative mechanism: time-varying exposures to systematic costs involved in the search for potential customers. This mechanism does not rely on capital or hiring frictions. In fact, the contribution of aggregate productivity shocks or operating leverage to the counterparty premium is quantitatively small. While Dou et al. (Forthcoming) 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 R/S spread is distinct from other production-based spreads, such as the productivity (Imrohoroglu and Tuzel 2014), inventory growth (e.g., Belo and Lin 2012; Jones and Tuzel 2013), investment (e.g., Titman, Wei, and Xie 2004), working capital (Wu, Zhang, and Zhang 2010), and distress (e.g., Griffin and Lemmon 2002) premiums.[2]

[2]Many studies, including Van Binsbergen et al. (2012), Eisfeldt and Papanikolaou (2013), Ai, Croce, and Li (2013), Segal (2019), Corhay, Kung, and Schmid (2020), Ai et al. (2020), Kogan, Zhang, and Zhu (2021), Grigoris and Segal (Forthcoming), and Davis and Segal (2022) connect expected returns to corporate policies.

Our findings are also related to recent advances in macroeconomics and finance that associate business cycle and asset price fluctuations to production networks. In particular, a firm's location in the production network and its relations with its peers can affect risk premiums. 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 that the counterparty premium is not explained by eigenvalue centrality, and is positive and significant within all layers of the production network. Herskovic (2018) examines the relation between network structure and aggregate consumption and shows that network concentration (sparsity) increases (decreases) marginal utility. Relatedly, we find that lower credit reduces the expected life span of supplier-customer relationships. This has an aggregate implication: lower aggregate trade credit makes the network less dense, by decreasing the number of surviving links. Herskovic et al. (2020) show that a supplier's risk is related to the concentration and idiosyncratic volatility of its customers. We find no differences in either customer 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.[3]

1 Empirical Facts

1.1 Data

Our study combines several data sources. Monthly stock return data are from CRSP, and accounting data, such as trade receivables and sales, are from the CRSP/Compustat Merged Fundamentals Annual file. Asset pricing factors related to the Fama and French (1993, 2015) three- and five-factor models, and the Carhart (1997) four-factor model, are from the data library of Ken French. Data related to the Hou et al. (2021) q^5-factor model are from the Global-q library. Section IA.1 of the Internet Appendix defines all variables used in this paper.

[3]Other studies that examine the pricing implications of production networks include the works of Branger et al. (2018), Ready, Roussanov, and Ward (2017), Ozdagli and Weber (2018), and Richmond (2019). However, these studies do not consider the role of trade credit in network dynamics.

Our sample includes the common stock (CRSP SHRCD 10 or 11) of all public firms in the CRSP/Compustat universe that are listed on the NYSE, AMEX, or NASDAQ exchanges (CRSP EXCHCD one, two, or three), excluding financial firms (SIC 6000–6999) and public utilities (SIC 4900–4999). We focus on the years ranging from 1978 to 2020 because data on trade receivable are sparse prior to 1978.

Firm-level data on supplier-customer relationships are obtained from the FactSet Revere database.[4] This novel data set provides comprehensive coverage of interfirm links using information from accounting statements, press releases, investor presentations, corporate announcements, and firms' websites. Importantly, by reporting both the start date and the end date of each supplier-customer link, the FactSet data allow us to measure link duration. This then allows us to document how trade credit usage is related to the dynamics of interfirm links.[5]

1.2 Fact 1: Trade credit and expected returns

This section shows that trade credit is informative about firm-level risk. We document that firms that offer more trade credit to their customers command lower risk premiums and are therefore safer.

1.2.1 Portfolio formation based on trade credit provision.

When firms sell goods to customers, they do not typically receive cash on delivery since a significant portion of goods are sold on credit. This extension of credit is an important tool for establishing supplier-customer relationships as firms offer credit to attract buyers, particularly when attempting to enter new markets or steal market share from competitors. The amount of credit offered is determined by weighing the expected losses from uncollectible accounts against the expected profits obtained by

[4]We follow the procedure outlined in Gofman, Segal, and Wu (2020) for cleaning and linking the FactSet data to CRSP/Compustat. Specifically, we exclude financial firms (GICS code 40) and industrial conglomerates (GICS 201050) and only retain suppliers that trade with more than one customer. The last filter removes any seasonality in FactSet's reporting and ensures we focus on the most economically relevant firms, as well as ensuring comprehensive coverage. Nonetheless, we verify that removing this data filter does *not* materially change our main results. We thank Youchang Wu for linking Compustat data with the FactSet database.

[5]The FactSet data are suitable for the study and duration measurements, since alternative data sources for supplier-customer relationships are either not as granular as FactSet (e.g., Compustat Segments data only report a supplier's largest customers at the annual frequency) or do not specify when interfirm 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 Compustat Segments database has fewer than 2,500 supplier-customer links covering fewer than 1,000 customer firms in the same year.

extending credit (see Dyckman, Magee, and Pfeiffer 2014). Notably, when a customer faces financial difficulties, suppliers are among the last creditors to be repaid and are often not paid in full.

Under Generally Accepted Accounting Principles (GAAP), supplier firms report revenues (Compustat item SALE) when they are *earned*, not when cash is collected. As such, suppliers add trade receivables (Compustat item RECTR) to their balance sheets to reflect the value of any sales made on credit.[6] Accordingly, we measure the trade credit provision of firm i in year t as

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

This ratio is often used to assess the effectiveness of a company's credit provision policies, and ability to collect cash from sales made on credit. This ratio multiplied by 365 is also known as "days receivable" in financial accounting. We exclude observations for which $R/S_{i,t}$ is zero, as firms that report zero trade credit almost never extend any trade credit to their customers.

We form portfolios by sorting the cross-section of firms on the basis of the R/S ratio. Specifically, at the end of each June in year t from 1978 to 2020, we form portfolios based on the values of R/S in the fiscal year ending in calendar year $t-1$. This lag between the release of accounting data and the June sort dates ensures this strategy is tradable. Each portfolio is then held from July of year t to the end of June of year $t+1$, when all portfolios are rebalanced.

We form three portfolios on each sort date. The low (high) R/S portfolio includes all firms with R/S ratios at or below (above) the $10th$ ($90th$) percentile of the cross-sectional distribution of R/S ratios in year $t-1$. The medium portfolio includes the remaining firms with R/S ratios between these two breakpoints. The low and high R/S portfolios are well-diversified as each contains about 330 firms. The mean firm-level R/S ratio is about 23%, and there is a large degree of cross-sectional variation in trade credit provision: the R/S ratio of the low (high) R/S portfolio is 3% (50%).

Firm-level trade credit provision varies not only across firms but also over time for each firm as firms can substantially alter the amount of trade credit they extend to their customers. Table IA.6.6

[6] A firm that has factored (or sold) its trade credit to a bank or another financial institution will not report the value of the trade credit that has been sold on its balance sheet. This is because the bank or financial institution has accepted all responsibility for collecting the credit from the customer firm. However, a firm may disclose whether the trade credit has been pledged as collateral for short-term loans on the footnotes to its financial statements. We discuss the implications of trade credit factoring for our results in Section IA.2.1 of the Internet Appendix.

of the Internet Appendix reports the annual transition probabilities between the R/S portfolios. The table shows that 85% of firms with low R/S maintain a low R/S ratio between successive years, but only about 60% of firms with high R/S continue to offer relatively large amounts of trade credit between years. Thus, while firm-level R/S ratios are generally persistent they are by no means fixed over time. This emphasizes the importance of the *conditional* annual rebalancing procedure.

1.2.2 The counterparty premium.

Portfolio returns. Panel A of Table 1 reports the monthly value-weighted returns of the R/S-sorted portfolios, using the formation procedure described in Section 1.2.1. The results indicate a monotonically decreasing relation between average returns and R/S.[7] Moreover, we document an economically and statistically significant spread between the returns of low and high R/S firms. The portfolio of firms that extend a low (high) amount of trade credit to their customers earns an average return of 1.25% (0.62%) per month. Consequently, the return spread between low and high R/S portfolios is about 0.64% per month and is statistically significant at the 1% level. The annualized Sharpe ratio of this spread is about 0.55. We label the approximately 7.6% p.a. difference between the returns of low and high R/S firms the *counterparty premium.*

To ensure that this premium is not driven by ex ante differences in the intensity of trade credit usage across industries, we also use *industry-adjusted* R/S ratios, denoted by $R/S_{i,t}^{IA}$, to form portfolios. We industry adjust the R/S ratio of firm i in Fama-French 30 industry j at time t by subtracting the cross-sectional median R/S ratio across all firms in industry j at the same point in time. Panel B then repeats the former analysis when we use R/S^{IA} as the sorting variable. The results are nearly identical to those in panel A as the industry-adjusted counterparty premium is 0.61% per month.

The relation between R/S and expected returns imposes a challenge vis-à-vis two hypotheses that predict opposite relations between trade credit and risk. From the perspective of financial statement analysis, high R/S firms are often perceived as having lower operating efficiency and higher exposures to shocks that deteriorate their customers' financial conditions. As defaults tend to occur during eco-

[7] We formally test the monotonic pattern between R/S and stock returns using the monotonicity test proposed by Patton and Timmermann (2010). By sorting firms into deciles and applying the test, we reject the null hypotheses that average returns are flat across all 10 R/S-sorted portfolios with a p-value lower than 5%. We obtain a similar result using portfolios sorted on industry-adjusted R/S ratios.

nomic downturns, this hypothesis suggests that high R/S firms should command higher risk premiums, in contrast with the data. The sign of the counterparty premium supports an alternative hypothesis that endogenously safer firms choose higher levels of R/S. Nonetheless, the risk of low R/S firms is anomalous from the perspective of extant asset pricing factors, as shown below.

Factor-model α's. We examine whether the counterparty premium is explained by common unconditional factor models. To do so, we project the monthly returns of the value-weighted R/S spread from panel A of Table 1 on the factors underlying five asset pricing models: the capital asset pricing model (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. (2021) q^5-factor model. The results in Table 2 show that the monthly α's obtained from these projections are always greater than 0.50% per month, and are statistically significant at the 1% level. These results demonstrate that the counterparty premium contains some time-series variation that is orthogonal to the variation in size, book-to-market ratios, investment, and profitability, among other factors.

Portfolio characteristics. We examine key CRSP/Compustat characteristics of the R/S-sorted portfolios. For the purpose of brevity, the details and subsequent analyses are relegated to Section IA.2 of the Internet Appendix. In particular, Table IA.2.1 shows that the low and high R/S portfolios are indistinguishable in terms of size, book-to-market ratios, investment and inventory growth rates, idiosyncratic return volatility, or the Hadlock and Pierce (2010) index of financial constraints. However, the low R/S portfolio contains firms with both higher profitability and stock return momentum than firms in the high R/S portfolio. Section IA.2.2 demonstrates that our spread is not driven by either of these characteristics using portfolio double sorts and Fama-MacBeth regressions. Lastly, use these portfolio characteristics to discuss and rule out potential mechanisms for the counterparty premium that impose an alternative to the one we offer in Section 2.

Robustness. Section IA.6 in the Internet Appendix reports a battery of robustness tests related to Tables 1 and 2: Tables IA.6.7 and IA.6.8 show that the counterparty premium remains significant using alternative breakpoints (e.g., terciles or quintiles); Table IA.6.9 reports the premium using equal-weighted returns; Table IA.6.10 shows that the premium persists within the recent half of our sample period; Table IA.6.11 documents that the spread persists if we scale a firm's trade receivables in Equation (1) by its average sales over the past 2 years.

Notably, Table IA.6.12 shows that our results are materially unchanged if we compute portfolio breakpoints using NYSE-listed firms only. Tables IA.6.13 and IA.6.14 report the premium, including observations where $R/S_{i,t} = 0$, and with NYSE breakpoints. Finally, Table IA.6.15 establishes that we obtain economically large and statistically significant α's if we reproduce Table 2 using the returns from the R/S spread constructed using (a) industry-adjusted R/S ratios from panel B of Table 1, (b) NYSE firms to define portfolio breakpoints, and (c) both industry-adjusted R/S ratios and NYSE breakpoints (including and excluding microcaps).

1.2.3 Trade credit and asset pricing factors.

Table 2 shows that the counterparty premium is mostly unrelated to common asset pricing factors. In line with this result, we establish that a risk factor that is based on the returns of the R/S-sorted portfolios is priced in the cross-section of equities beyond known factors and carries a negative and statistically significant market price of risk. Section 2.1 provides an economic interpretation for this reduced-form factor. We establish this fact using both the traditional generalized method of moments (GMM) approach and the more recent method proposed by Feng, Giglio, and Xiu (2020).

GMM. We posit that the stochastic discount factor (SDF) that prices all assets in the economy is given by

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

We measure the counterparty risk factor, CPR, using the spread between the value-weighted returns of the portfolio that buys high R/S firms and sells low R/S firms.[8] b_{CPR} is the parameter of interest that measures the market price of risk associated with CPR. $\boldsymbol{b}$ is a $k \times 1$ 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

[8]This specification of the SDF will be later supported by the evidence in Section 2.2 and our theoretical model in Section 3. Specifically, our evidence suggests that systematic shocks that affect the cost of searching for new customers can explain the R/S spread. While all firms are negatively exposed to these systematic customer-search cost shocks, low R/S firms have the most negative exposure. Consequently, a portfolio that buys high R/S firms and shorts low R/S firms has a *positive* exposure to these search shocks and the price of risk of CPR shares the same sign as the price of risk of these underlying search cost shocks. This type of linear SDF specification is widely used to test the price of new fundamental factors (see, e.g., Papanikolaou 2011; Lin, Palazzo, and Yang 2020).

or the Fama and French (1993) three factors.[9] For the purpose of supporting our model, we only need to demonstrate that CPR affects the SDF beyond aggregate productivity (i.e., beyond the CAPM). Finally, all factors underlying Equation (2) are demeaned.

We estimate the factor loadings in Equation (2) by GMM using the following moment conditions:

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

where $r_{i,t}^e$ 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 risk factor loadings using 25 value-weighted portfolios double sorted on size and book-to-market. Second, we follow the suggestion of Lewellen, Nagel, and Shanken (2010) and also estimate the factor loadings using a set of 74 portfolios that augments the first set of test assets with the Fama-French 49 value-weighted industry portfolios. This allows us to break the strong factor structure inherent in the returns of the first set of test assets. Third, we also estimate the factor loadings using a comprehensive set of 154 portfolios that augments the second set of test assets with 10 value-weighted portfolios sorted on each of investment, profitability, momentum, market betas, stock issuance, accruals, variance, and residual variance.

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 risk factor are consistently negative, and are always statistically significant at better than the 1% level. In particular, if all 154 test assets are included in the estimation, then the market price of counterparty risk in panel A (panel B) is -8.36 (-6.94). The table also shows that adding the counterparty factor to the CAPM or the Fama and French (1993) model can reduce the MAE of these models by as much as 19%.

[9] In Table IA.6.16 of the Internet Appendix, we modify the vector $\boldsymbol{f}_t$ to include all five factors of Fama and French (2015). The results are materially unchanged.

Feng, Giglio, and Xiu (2020) test. We examine whether the CPR factor is priced using the machine learning-based test that Feng, Giglio, and Xiu (2020) propose to "tame the factor zoo." This allows us to condition on over 100 known predictors of returns and ask whether CPR provides an *incremental* ability to explain the cross-sectional variation in expected returns. The results confirm that the counterparty risk factor has a negative and statistically significant SDF loading. Namely, the SDF loading is -0.79 per month (t-statistic of -2.19). Similarly, the SDF loading is -0.85 (t-statistic of -2.01) when we construct the factor using only NYSE-listed firms to define portfolio breakpoints, and -0.80 (t-statistic of -2.24) when we exclude microcap firms.

1.3 Fact 2: Trade credit and the production network

Trade credit provision involves both a supplier firm that offers the credit and a customer firm that promises to repay the credit. Therefore, it is natural to examine the differences between high and low R/S firms through the lens of the production network. We establish that trade credit is informative about the duration of supplier-customer relationships (links). At the micro-level, firms that offer less trade credit maintain shorter relationships with their customers. At the macro-level, aggregate trade credit positively predicts the production network's density.

1.3.1 Network characteristics.

We begin by examining whether high and low R/S firms differ in terms of key network-based characteristics that are known to predict future returns. Prior papers have established that eigenvalue centrality (Ahern 2013), upstreamness (Gofman, Segal, and Wu 2020), and customer concentration and volatility (Herskovic et al. 2020) are associated with risk premiums. In addition, we also consider a key network-related characteristic that is largely overlooked by existing network studies: the average duration (in months) of a supplier's links with its existing customers. The construction of each of these network-related characteristics is described in Section IA.1 of the Internet Appendix.

Table 4 reports the results. The low and high R/S portfolios have similar degrees of eigenvalue centrality. Consistent with Gofman and Wu (Forthcoming), we confirm that high R/S firms are typically more upstream producers than low R/S firms. However, we note that this cannot account for fact 1, as Gofman, Segal, and Wu (2020) show that more upstream firms earn *higher* returns. In contrast, Table 1 documents that high R/S firms earn *lower* risk premiums. Similarly, there are also no significant differences in terms of either the concentration or the idiosyncratic volatility of each constituent firm's customer base. Thus, none of the former four characteristics can reconcile fact 1 (the counterparty premium).[10]

The last row of Table 4 does, however, indicate a key difference between high and low R/S firms in terms of link duration. High R/S firms maintain their supplier-customer relations for about eight months longer than low R/S firms. This is economically sizable as the median link's duration is about 4 years. Below, we will examine the implications of trade credit for the life span of interfirm links.

1.3.2 Trade credit and link duration.

In this section we empirically explore the economic importance of trade credit provision for the expected duration of supplier-customer relationships. Our main finding is that firm-level trade credit provision positively forecasts the duration of existing supplier-customer links. We also show that, at the macro-level, 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 for which FactSet data are available, 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 break in the future. Specifically, the indicator takes on a value of one if the majority of the supplier's links (i.e., 50% or more) that exist in year t do not survive until year $t+4$. The choice of $t+4$ is motivated by the fact that the average duration of supplier-customer links is about 4 years (see Table 4). The industry-adjusted supplier-level characteristics, denoted by $\mathbf{X_{s,t}}$, used to predict $D_{s,t}$ include the R/S ratio, the

[10]The fact that there are no differences between the low and high R/S portfolios in terms of eigenvalue centrality or customer concentration also rules out the possibility that differences in bargaining power drive the counterparty premium. We provide additional evidence on this point in Section IA.2.1 of the Internet Appendix.

number of customers associated with each supplier, the supplier's investment rate and profitability, the natural logarithm of the supplier's market value and book-to-market ratio, and the backward-looking (or "lagged") duration of supplier-customer links. Thus, the cross-sectional regression is

$$D_{s,t} = const + \boldsymbol{\beta}_t \boldsymbol{X'_{s,t}} + \varepsilon_{s,t} \quad \forall t \in \{2003, \ldots, 2020\}. \tag{4}$$

Estimating Equation (4) on an annual 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 coefficient $\hat{\boldsymbol{\beta}}_t$ across all years, and report the average slope coefficients in Table 5. Each predictor is scaled by its unconditional standard deviation for ease of interpretation.

Panel A of Table 5 shows that while the future duration of existing links is difficult to predict, increases in the amount of trade credit offered are associated with significantly longer supplier-customer links.[11] A one-standard-deviation increase in R/S predicts that link duration will rise by about four months, and this effect is statistically significant at the 1% level. Moreover, the slope coefficient for R/S shows that trade credit has the largest marginal effect on link duration compared to other supplier-level controls, including profitability, investment rate, and size. We note that if firms simply extend more trade credit to customers they already have a long relationship with, then trade credit should play no role in explaining the future duration of links once lagged duration is controlled for. However, this is not the case: R/S has predictive power for future link duration *beyond* existing link duration.

Panel B of Table 5 yields similar results and shows that increases in R/S are associated with a reduced probability of supplier-customer links breaking: a one-standard-deviation increase in a supplier's R/S reduces the likelihood of breaking by 9%. The slope coefficient for R/S has a similar magnitude to that of lagged duration, and R/S is the most economically important predictor of the link-break probability among the remaining supplier-level characteristics. For instance, a one-standard-deviation increase in profitability only reduces the same likelihood by 2%, and the effects of

[11] Table IA.6.17 in the Internet Appendix repeats the analyses by estimating panel regressions featuring year fixed effects and excluding low-sales firms. The table indicates that R/S retains an economically large and statistically significant association with future link duration, and the R^2 increases to 21%.

book-to-market and the investment rate are statistically insignificant.

In principle, the number of customers can affect the incentive to allocate trade credit, as the customer base is more diversified. To check the sensitivity to this diversification motive, we consider all results with and without controlling for the number of customers. Table 5 shows that this additional control has virtually no affect on the marginal contribution of R/S for future link duration, which guides our modeling assumptions in Section 3.

The role of trade credit in prolonging supplier-customer links is consistent with extant studies in corporate finance (Petersen and Rajan 1997; Cunat 2006; Wilner 2000; Garcia-Appendini and Montoriol-Garriga 2013; Costello 2020), showing that trade credit provides liquidity to customers in times of crisis and helps to stabilize the financial conditions of customers. Equivalently, as trade credit is paid in the future, it can be perceived as a discount on sales that persuades a customer to keep its relation with its current supplier.

Macro-level analysis. The former micro-level evidence implies that the average level of R/S should positively predict the density of the production network, as more existing relationships are expected to remain active in the future. Section IA.3 in the Internet Appendix confirms this conjecture. Our analysis shows that a one-standard-deviation increase in aggregate R/S predicts that the 1-year-ahead network density will rise by about 3% to 9% relative to its mean (depending on the set of controls). The predictive power of the aggregate R/S ratio is economically sizable and statistically significant up to eight-quarters ahead. Furthermore, the significance of trade credit in predicting future network density once again extends beyond that of lagged density.

2 Explaining the Facts: Data

To explain facts 1 and 2, we start by laying out a risk-based hypothesis that connects trade credit to the dynamics of the production network's linkages. We then substantiate the hypothesis in two steps. In the first step, we use the hypothesis to derive a rich set of *qualitative* predictions, and confirm them empirically. In the second step, we formalize the hypothesis using a production-based model to *quantitatively* demonstrate that the risk-based narrative can reproduce the various empirical findings.

Hypothesis: Trade credit as a hedge for costly search. *Assume that searching for new customers is risky, as searching entails systematic costs that rise during high marginal utility states. Trade credit is used to prolong relations with good customers, and thereby decreases the exposure to risks associated with customer search and replacement. Consequently, firms extending more trade credit have lower risk premiums (fact 1) and longer duration relationships with their customers (fact 2).*

The above hypothesis yields six prominent predictions.

1. Aggregate motive for extending trade credit: The total amount of trade credit in the economy increases with macro conditions that increase the expected cost of searching for customers.

2. Aggregate fluctuations in trade credit explain the counterparty premium: Since aggregate trade credit is highly correlated with customer search costs (prediction 1), it should explain the return spread between low and high R/S firms. Furthermore, both return and cash flow exposures to aggregate trade credit are negative, and the market price of risk associated with aggregate trade credit is also negative, consistent with search costs rising in high marginal utility states.

3. Customer search affects cash flows: In line with the negative exposures (prediction 2), firms that engage in the search for new customers have lower profits.

4. Idiosyncratic motive for extending trade credit: Holding the amount of systematic search-costs constant, firms extend more trade credit to better-quality customers that are worth retaining.

5. Link-duration premium: All else equal, firms with lower duration links with their customers have higher expected returns due to their greater exposure to systematic customer-search costs.

6. The cost of trade credit: while extending trade credit is costly, as it exposes firms to greater default risk, the benefit of hedging against costly search dominates for firms' risk premiums.

Predictions 1–5 are subsequently tested in Sections 2.1–2.5, while Prediction 6 is theoretically confirmed in Section 3.

2.1 Prediction 1: Aggregate motive for extending trade credit

Whenever the search costs associated with finding a new customer rise, all firms have a greater incentive to hedge against these costs by allocating more trade credit to their customers. Consequently, the aggregate amount of trade credit (or equivalently, its cross-sectional average) should covary with the degree of customer search costs. To empirically demonstrate that the aggregate amount of trade credit does indeed proxy for search costs, we consider two observable sources of variation in these costs: anticipated changes in the number of new firms entering the economy and changes in the degree of competition among suppliers.

On the one hand, the costs involved in the search for a new customer can rise when the pool of potential customers is expected to shrink. With fewer potential customers looking for a supplier, it takes longer for a supplier to find a counterparty, resulting in a more costly search process. In practice, the pool of potential customers may shrink for many reasons, including an expected decline in the number of newly created firms that are naturally searching for a supplier upon entering the economy. On the other hand, an increase in the cost of matching with a customer may reflect an increase in competition among suppliers. Several factors can reduce a supplier's market power, such as a lower degree of substitutability between products, lower barriers to entry, higher spillovers of knowledge, or the departure of key talent (Dou et al. Forthcoming). For these reasons, when suppliers have lower market power, potential customers have relatively more bargaining power and can squeeze more rents from the supplier. This leads to higher matching costs for suppliers searching for new customers.

Following the discussion above, we examine the relation between these two proxies of aggregate search costs and the average receivables-to-sales ratio across all firms in year t, denoted by $\overline{R/S}_t$, via

$$\overline{R/S}_t = \rho_0 + \rho_{SC}\text{SearchCost}_t + \rho_{TFP}\text{TFP}_t + \varepsilon_t. \tag{5}$$

Here, the aggregate TFP, measured using the utilization-adjusted TFP from Fernald (2012), controls for business cycle fluctuations that may drive part of the variation in trade credit extension.

Our first measure of search costs, $DeathMinusBirth_t$, is the time-t predictable component of the future death-minus-birth rate of establishments from the BLS. We obtain the expected component of this rate by regressing the 1-year-ahead death-minus-birth rate onto its own lag and the excess market returns and the corporate default spread at time t. When the anticipated death-minus-birth rate over the next period increases, the pool of firms looking for a potential supplier is expected to shrink, and the search costs rise.

Our second proxy, $RelativeCompetition_t$, captures the competitiveness of suppliers relative to customers and is constructed in three steps. First, we partition firms into three groups each year based on the top and bottom $30th$ percentiles of BEA-implied upstreamness scores from Gofman, Segal, and Wu (2020). The former group represents supplier-oriented firms, while the latter group represents customer-oriented firms. Next, we compute the Herfindahl-Hirschman index (HHI) 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 both contemporaneously and predicatively as the difference is persistent. These are situations in which the cost of a supplier matching with a customer is likely to be higher, as suppliers are more competitive than customers.

Table 6 reports the results. TFP alone as an insignificant correlation with $\overline{R/S}_t$. However, controlling for TFP, columns 2 and 3 show that the partial correlation between $DeathMinusBirth_t$ and $\overline{R/S}_t$ is 0.4 and statistically significant at the 1% level. Similarly, the correlation between $RelativeCompetition_t$ and $\overline{R/S}_t$ in columns 4 and 5 is over 0.5 and also significant at the 1% level. Motivated by these findings, the subsequent sections use the aggregate receivables-to-sales ratio ($\overline{R/S}_t$) as an observable proxy for customer search costs. Importantly, aggregate trade credit should still rise if some aspects of these search costs are unobservable. We later confirm that this proxy is indeed tightly related to search costs through the lens of the production-based model in Section 3.

2.2 Prediction 2: Aggregate trade credit explains the counterparty premium

We examine if the counterparty premium is explained by exposures to various macroeconomic shocks. We posit the following two-factor empirical SDF specification:

$$M_t = 1 - b_{MKTRF} MKTRF_t - b_{MACRO} MACRO_t, \tag{6}$$

where $MKTRF_t$ is the excess market return and $MACRO_t$ represents a proxy for a second aggregate shock. We consider the following candidates for $MACRO_t$: (a) innovations to the aggregate receivables-to-sales ratio ($\overline{R/S}$), which we measure using its log first difference, (b) innovations to the utilization-adjusted TFP from Fernald (2012) (TFP), also measured by the log first difference, (c) the corporate default spread (DEF), (d) macroeconomic uncertainty from Jurado, Ludvigson, and Ng

(2015) (UNC), (e) investment-specific technology shocks proposed by Papanikolaou (2011) (IST), (f) intermediary capital from He, Kelly, and Manela (2017) (INT), and (g) the equity cost issuance shock from Belo, Lin, and Yang (2019) (ESC). Our primary test assets are the 10 value-weighted R/S-sorted portfolios from Section 1.2. We use GMM to estimate the risk factor loadings on the two aggregate shocks based on the Euler condition $\mathbb{E}\left[M_t r_{i,t}^e\right] = 0$, which we rewrite as

$$\mathbb{E}\left[r_{t,t}^e\right] = \alpha_i + b_{MKTRF}\text{Cov}\left(r_{i,t}^e, MKTRF_t\right) + b_{MACRO}\text{Cov}\left(r_{i,t}^e, MACRO_t\right). \quad (7)$$

Here, $r_{i,t}^e$ is the excess return of test asset i in year t, α_i is the pricing error of asset i, and b_{MKTRF} and b_{MACRO} are the prices of risk for the excess market return and the macroeconomic shock, respectively.

Table 7 reports the results. For the purpose of brevity, we report the pricing errors (panel A) and the returns' covariance with the macroeconomic factor (panel B) for the low (L, or decile 1), medium (M, or decile 5), and high (H, or decile 10) R/S portfolios, and for the spread portfolio that takes a long position in portfolio L and a short position in portfolio H. The leftmost column omits the macroeconomic shock, such that the SDF reduces to the CAPM. In all other columns, the SDF includes both the market factor and one of the macroeconomic shocks listed above.

Pricing errors. We highlight four key observations. First, the market factor alone cannot explain the counterparty premium, as the pricing error for the spread in the leftmost column is 9.97% p.a. and significant at the 1% level. This echoes the results reported in Table 2, which shows the failure of the CAPM to explain the R/S spread. Second, and with the exception of aggregate trade credit, no macroeconomic factor can explain the counterparty premium as the pricing errors associated with the R/S spread are nonzero and statistically significant at the 10% level or better. This finding broadly reflects the failure of existing multifactor models to explain the counterparty spread in Table 2.

Third, $\overline{R/S}$ innovations are the only macroeconomic shocks that can explain R/S spread. Using this macroeconomic factor reduces the pricing error of the spread to only -0.84% p.a., a quantity that is statistically indistinguishable from zero. Economically, this pricing error is also the smallest among the comprehensive set of macroeconomic factors we consider. Fourth, the covariances of portfolio returns with $\overline{R/S}$ innovations monotonically decrease (in absolute terms) from the low to the high

R/S portfolio. The R/S spread has a covariance of -0.77 with the aggregate receivables-to-sales innovation that is significant at the 1% level. To the extent that changes in $\overline{R/S}$ reflect changes in the search costs for new customers (recall the evidence in Section 2.1), these findings are closely aligned with our risk-based hypothesis. Thus, fluctuations in $\overline{R/S}$ can reconcile the counterparty premium.

Prices of risk. Focusing on $\overline{R/S}$ as a macroeconomic factor, panel C reports the market prices of risk associated with $MKTRF$ and $\overline{R/S}$ innovations. Here, the test assets are either (a) the 10 R/S-sorted portfolios utilized in panels A and B or (b) a broader set of assets that also includes the five Fama-French industry portfolios, six portfolios sorted on size and book-to-market, six portfolios sorted on size and profitability, and six portfolios sorted on size and investment. b_{MKTRF} is positive and significant regardless of whether the market factor is the only risk factor in the SDF or is used in conjunction with $\overline{R/S}$ innovations. The market price of risk associated with $\overline{R/S}$ innovations is -14.50 when the test assets only include the 10 R/S-sorted portfolios and remains -6.91 among the broader set of test assets. In both cases, these prices of risk are statistically significant at better than the 1% level. This finding lends support to the hypothesis that an increase in the search costs for new customers, as reflected by an increase in $\overline{R/S}$, signals a high marginal utility state for investors.

Interpreting the evidence. Figure 1 plots the aggregate receivables-to-sales ratio $\overline{R/S}$ and its innovations. Focusing on the innovations used for estimating Equation (6), we note that the correlation between these innovations and $MKTRF$ is barely 0.16, and statistically insignificant (the 95% confidence interval is [-0.13, 0.45]). Consistently, the figure shows no clear cyclicality for the innovations to $\overline{R/S}$. For instance, while the innovation to $\overline{R/S}$ is quite negative during the Great Recession, it is equally as negative during the middle of the expansion period of the 2010s. Despite not featuring a contemporaneous correlation with the business cycle, Table IA.6.25 in the Internet Appendix shows that controlling for the market returns, innovations to $\overline{R/S}$ predict consumption growth negatively up to 3 years ahead. The impact of $\overline{R/S}$ innovations on future consumption is consistent with a negative price of risk (under recursive preferences with early resolution of uncertainty).

Furthermore, the negative market price of risk of aggregate trade credit innovations has an intuitive interpretation vis-à-vis the two drivers of higher customer search costs explored in Section 2.1. For instance, larger search costs that relate to a drop in the number of new firms are also likely to be associated with higher marginal utility. Since new entrants represent young firms with growth opportunities, a decrease in the cohort of new firms can significantly and persistently reduce aggregate productivity, and therefore decrease economic growth. Clementi and Palazzo (2016) show that lower entry amplifies macroeconomic shocks, leading to bad economic states. Likewise, higher search costs that are driven by an increase in supplier-level competition are also likely to raise the marginal utility of investors. An increase in supplier-level competition can lead to larger displacement, which is associated with a negative price of risk (see, e.g., Gârleanu, Kogan, and Panageas 2012; Loualiche 2019; Kogan, Papanikolaou, and Stoffman 2020).

To support these conjectures, Table IA.6.26 in the Internet Appendix repeats the key GMM analyses using either $DeathMinusBirth_t$ or $RelativeCompetition_t$ as the macroeconomic factor in Equation (6). In either case, and for the subsample in which each variable is available, the pricing error of the R/S spread is insignificant, the covariance of the R/S spread with each macroeconomic factor is negative, and the resultant market price of risk is negative. This evidence further validates the notion that $\overline{R/S}$ acts as an observable proxy for customer search costs.

Cash flow sensitivities. To complement the evidence regarding the risk exposures of each R/S-sorted portfolio's returns in panel B, we also examine the cash flow exposures of these portfolios to $\overline{R/S}$ in panel D. The cash flow exposure of each portfolio is obtained via β_2 in the projection:

$$CF_{i,t} = \beta_0 + \beta_1 MKTRF_t + \beta_2 \overline{R/S}_t + \varepsilon_{i,t}. \tag{8}$$

Here, the cash flows of portfolio i in year t are denoted by $CF_{i,t}$ and are measured using the average dividend growth, dividends per share, or profitability, defined as EBIT-to-assets, of each portfolio. Each of these cash flow measures is industry-adjusted. Consistent with the pattern of return exposures, the sensitivity of dividend growth to $\overline{R/S}$ varies from -0.34 for the low R/S portfolio to -0.01 for the high R/S portfolio. Notably, all cash flow measures indicate that the sensitivity of the low R/S portfolio is significantly lower than that of the high R/S portfolio, yielding a negative and significant cash flow exposure for the R/S spread. This evidence indicates that customer search is costly, which we further verify in the next section.

2.3 Prediction 3: Customer search negatively affects cash flows

Our risk-based hypothesis for the counterparty premium posits that searching for new customers is costly. Because of this cost, firms that match with new customers should incur a drop in their dividends, and/or an increase in their operating costs. We confirm that this is indeed the case in the data.

For each firm i and quarter t for which the FactSet data are available, we define an indicator $NC_{i,t}$ that equals one if 50% or more of the links between firm i and its customers at the end of quarter t are newly formed (i.e., did not exist at the end of quarter $t-1$). If $NC_{i,t}$ is one, then firm i engaged extensively in the search for new customers between times $t-1$ and t. We then examine whether the profits (costs) of the firms for which $NC_{i,t}$ is one are lower (higher) than those for which $NC_{i,t}$ is zero.

Table 8 reports the average profitability measures of firms that mainly retain their existing customers ($NC_{i,t} = 0$) versus those that mainly searched and matched with new customers ($NC_{i,t} = 1$). Consistent with the notion of costly search, we find that the dividends per share, net profit margins, and ROA are significantly lower for the group of firms with mostly new customers. The change in the net profit margin is particularly striking: whereas this ratio is 0.06 for firms that retain most of their customers, it is -0.22 for firms that recently searched for new customers, a decrease of 250% in absolute value.

The operating costs, as defined by Novy-Marx (2011), are considerably greater for $NC_{i,t} = 1$ firms compared to $NC_{i,t} = 0$ firms. This is broadly consistent with the finding of Gourio and Rudanko (2014), who document that firms with greater product market frictions pay higher expenses for customer acquisition (e.g., selling or marketing expenses), as proxied by SG&A, which is a component of the Novy-Marx (2011) measure. Lastly, we find that the TFP of firms that search for new customers is lower than that of firms that tend to retain old customers, consistent with the notion that suppliers already matched with high-quality customers do not search for new customers.

The previous analysis assumes that firms experience an operational cost whenever they *search* for new customers. While searching for customers can occur for any growing firm, the search is particularly costly if it is initiated in response to a link with an existing customer breaking. That is, *replacing* a previous customer with a new customer should be costly as well. Adhering to this alternative interpretation, we construct a measure of customer replacement that is defined as the minimum of (a) the number of links with previous customers that break, and (b) the number of links with new customers that form, between times $t-1$ and t. This measure is only positive if a new supplier-customer link forms in the same period that an old link breaks. Similar to Table 8, Table IA.6.18 in the Internet Appendix shows that firms with more customer replacements have lower profitability and productivity, as well as higher selling and marketing costs.

2.4 Prediction 4: Idiosyncratic motive for extending trade credit

Conditional on aggregate search costs, which firms should extend more trade credit to their customers? If, as we hypothesize, firms extend trade credit as a means of encouraging their customers to keep their business with the firm, then more trade credit will be offered to better-quality customers.

We compute the correlations between supplier-level receivables-to-sales ($R/S_{s,t}$) and average customer-level quality ($Q_{c,t}$) using Fama-MacBeth regressions. First, in each year for which the production network data from FactSet are available (2003–2020), we identify the set of active supplier-customer relationships. Next, we estimate a cross-sectional regression at June of every year t

$$Q_{c,t} = \alpha_t + \rho_t R/S_{s,t} + \varepsilon_{c,t}. \tag{9}$$

Here, each firm-level characteristic is standardized by its unconditional standard deviation. This means that the slope coefficient ρ can be interpreted as the correlation between $Q_{c,t}$ and $R/S_{s,t}$. Finally, we compute the time-series average ρ_t obtained by estimating Equation (9) each year.

Our main measure of quality ($Q_{c,t}$) is each customer's firm-level TFP from Imrohoroglu and Tuzel (2014). The time-series average correlation between customer-level TFP and supplier-level R/S is 0.18 and statistically significant at the 1% level (t-statistic of 15.11). Consequently, R/S is indicative about the average productivity of the firm's current customer base, a property that is difficult to observe. We complement this evidence by considering two other proxies for customer quality: each customer's sales-to-employment ratio, a proxy for labor productivity, and ROE, a proxy for profitability. In line with the previous finding, the time-series correlations between $R/S_{s,t}$ and each of these two other measures of quality are about 0.10 and significant (t-statistics of 3.17 and 2.76, respectively). Collectively, these correlations are consistent with Gofman and Wu (Forthcoming), who show that suppliers provide more trade credit to more profitable customers. Motivated by this evidence, productivity is the economic primitive that drives differences in customer quality across firms in Section 3.

2.5 Prediction 5: Link duration premium

If customer turnover is risky, then firms that maintain longer-duration relationships with their customers should be safer as they will not incur the systematic customer search costs. Thus, cross-sectional differences in the duration of links with customers should manifest themselves as differences in expected returns. We examine this by conducting a portfolio sort using the link duration characteristic, and we implement this sort using the same portfolio formation procedure described in Section 1.2.1 with two exceptions. First, the sorts begin in April 2003 given the availability of the FactSet data. Second, we rebalance the portfolios monthly instead of annually to offset losses in statistical power from the shorter sample period. Panels A and B of Table 9 present the results.

We find an economically large, statistically significant, and novel spread associated with the average life of supplier-customer links. Suppliers that have shorter-lived links with their customers earn average value-weighted returns that are 0.98% per month higher than those earned by suppliers that maintain longer-lived links. The link duration premium also aligns with the counterparty premium, as low R/S firms maintain low duration links with their customers (recall Table 4). We therefore investigate whether the macroeconomic variable that explains the counterparty premium and proxies for search costs—$\overline{R/S}$—also explains the link-duration spread. We report this analysis in panels C and D of Table 9. Using the SDF in Equation (6) and setting $MACRO_t$ to $\overline{R/S}$ innovations shows that the pricing error for the link-duration spread is insignificant.

3 The 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 formalize the risk-based hypothesis from Section 2 to quantitatively explain facts 1 and 2 from Sections 1.2 and 1.3, respectively. Specifically, does exposure to systematic search costs for new customers impose enough *quantitative* power to reconcile the counterparty premium without calibrating the model frictions to target this premium? Does lower customer search risk dominate higher customer default risk for firms that extend more trade credit?

The model features a continuum of supplier firms, each of which offers trade credit to its counterparty, namely, a customer firm. The quality of customer firms is heterogeneous, with a better customer increasing the revenue of its supplier. While customers may exogenously depart, trade credit reduces the likelihood of these departures (by providing, e.g., liquidity insurance or a discount on sales). However, extending trade credit is costly: the supplier incurs an opportunity cost of forgoing current cash flows and faces the risk that the customer will not repay the credit in bad states.

3.1 Production, technology, and investment

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

$$Y_{it} = (A_t C_{it})^{1-\alpha} K_{it}^{\alpha}, \tag{10}$$

where K_{it} is 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 (representative) customer of firm i. Note that we depart from the standard literature by assuming that Y_{it} is partially determined by the productivity of a firm's customer (counterparty). Specifically, C_{it} can be thought of as the productivity of the supplier-customer pair. Ample evidence points to productivity spillovers or synergies created during production, and we provided evidence along these lines in Section 2.4. Alternatively, the output of the supplier can be treated as a distinct and not perfectly substitutable input to the customer. In this case, C_{it} can represent markup that the supplier charges the customer for selling a specialized product.

The logarithm of the aggregate productivity process follows a random walk

$$\log A_{t+1} = \log A_t + \mu_a + \sigma_a \varepsilon^a_{t+1}, \tag{11}$$

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 outside opportunities for capital. Moreover, the firm also chooses investment I_{it} so that capital accumulates according to

$$K_{it+1} = (1 - \delta) K_{it} + I_{it}, \tag{12}$$

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 $K_{it}\phi(I_{it}, K_{it})$, where

$$\phi(I_{it}, K_{it}) = b\left(\frac{I_{it}}{K_{it}} - \delta\right)^2. \tag{13}$$

3.2 Counterparty and trade credit

3.2.1 The role of trade credit and the termination of links.

A high-quality counterparty—captured by a high value of C_{it}—helps to increase the output produced by the supplier, Y_{it}. However, counterparties can experience idiosyncratic shocks that cause the supplier-customer relationship to terminate. We posit that greater trade credit allocation to the customer decreases the probability of link termination, consistent with the evidence in Section 1.3.2.

Two possible interpretations apply to these shocks and their relation to trade credit. First, these termination shocks can capture a strategic decision of the customer to switch to a different supplier. In this case, more trade credit can be interpreted as a discount, and the supplier competes with other suppliers by offering to delay collecting the payments. Second, these shocks can also capture a liquidity shock that causes the customer to default for various exogenous reasons (i.e., become insolvent for reasons unrelated to accounts payable) and terminates the supplier-customer relationship. Under this interpretation, trade credit provides liquidity insurance to the customer, and reduces the probability of a customer failing. Consistent with Wilner (2000), we opt for the second interpretation that introduces an explicit default risk in trade credit provision.

Consequently, we specify that the link between firm i and its current customer at time t will terminate (or default) at the beginning of time $t+1$ with probability

$$\Gamma_t(r_{i,t+1}) = \underbrace{\left[(\bar{p} - \underline{p})(1 - r_{i,t+1})^{\lambda} + \underline{p}\right]}_{\text{Idiosyncratic}} \cdot \underbrace{g(\Delta a_t)}_{\text{Systematic}}, \tag{14}$$

where $\bar{p}$ ($\underline{p}$) is the maximum (minimum) termination probability, controlling for the systematic component of the termination probability $g(\Delta a_t)$.

The systematic termination component satisfies $g'(\Delta a_t) < 0$ so that the probability of link termination due to customer default increases in low aggregate productivity states. In the baseline analysis we set $g(\Delta a_t) = \exp(\Delta a)^{\nu}$, where $\nu \leq 0$. λ is a convexity parameter that determines the rate at which the termination probability drops with $r_{i,t+1}$. Here, $r_{i,t+1} \in [0, 1]$ represents the amount of trade credit extended by firm i to its customer in period t, scaled by total sales in period t (i.e., R/S). This trade credit ought to be repaid in period $t + 1$. Consequently, higher $r_{i,t+1}$ can result from extending more trade credit in dollars (explicit liquidity provision) or providing a discount on sales as payment is delayed. Both interpretations raise $r_{i,t+1}$ and are equivalent from a modeling perspective.

We assume that choosing $r_{i,t+1}$ is at the discretion of firm i. This is motivated by the evidence presented in Section IA.2 of the Internet Appendix that rules out bargaining as a driver of the counterparty premium. Specifically, we show that there are no differences in common proxies for bargaining power, such as eigenvalue centrality (Ahern, 2013) and customer concentration, between low and high R/S firms. Relatedly, we assume that all customers have the same ex ante probability of default parameters, $\bar{p}$ and $\underline{p}$. This is motivated by the evidence in Table 4 showing the customers of low and high R/S firms do not differ in regards to their external loan terms.

The benefit of extending trade credit is that it reduces the probability of links breaking (i.e., $\Gamma_r < 0$). By offering more $r_{i,t+1}$, firm i provides more liquidity to its customer, partially insuring its customer and reducing the probability that its customer defaults.[12] This is similar to Cunat (2006). However, trade credit provision is also costly for suppliers. First, there is no interest due on trade credit that is repaid on time as is often the case empirically.[13] Second, the supplier pays an opportunity cost to forgo its current cash flows (i.e., the firm must reduce its current dividends and/or investment). Third, the supplier exposes itself to the possibility that its customer will default, precisely in bad states, and any outstanding credit will be lost. All else equal, this raises suppliers' costs of capital by

[12] In practice, the customer may have further sources of financing that provide liquidity, such as bank loans. We deliberately abstract from banks in our model, a step motivated by the evidence in Section IA.2 showing that the customers of low and high R/S firms do not differ across the various terms of their bank loans.

[13] In most trade credit contracts, there is no interest rate on trade credit that is paid on schedule. If the model introduced an interest rate, the cost of extending trade credit would drop. On one hand, this would increase the average level of R/S. On the other hand, this would not increase the cross-sectional dispersion of R/S, as all customers are ex ante identical in their default probability. Given that dispersion dictates the magnitude of the counterparty premium, interest rates are unlikely to have a quantitatively meaningful impact on our results.

commanding a default premium. Lastly, the loss of trade credit is especially costly for suppliers when the cost of searching for a new customer increases, as will be described below.

3.2.2 Customer search and replacement.

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

$$C_{i,t+1} = C_{i,t}. \tag{15}$$

If the current customer defaults, which happens with probability $\Gamma\left(r_{i,t+1}\right)$, then firm i cannot recoup its trade credit and needs to search for and match with a new counterparty. The new counterparty's quality is drawn from an i.i.d. pool such that:

$$\log C_{i,t+1} \sim \mathcal{N}\left(0, \sigma_c^2\right). \tag{16}$$

The search for a new counterparty is costly. 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) that is orthogonal to productivity shocks (ε_{t+1}^a). Specifically, we assume that

$$f_{t+1} = f_0 + \sigma_f \varepsilon_{t+1}^f, \tag{17}$$

where ε_{t+1}^f is an i.i.d. standard normal shock. This shock represents systematic counterparty risk in our model and captures fluctuations in the cost of searching for counterparties and establishing collaborations.

The payment of the cost f is motivated by the evidence in Section 2.3 that firms who search for new customers experience higher operating costs and lower profit margins. As shown in Section 2.2, these costs can fluctuate with customer entry or supplier competition.

Customer versus capital replacement risk. In our model, the costs associated with replacing customers or retaining good customers are distinct from the costs associated with replacing or maintaining physical capital. First, trade credit provision is related to the *flow* of output, and the customer's quality does not decay. In contrast, investment is related to the *stock* of capital which depreciates. Second, a customer default on trade credit is associated with the loss of *past* revenues, while retiring machines only affects *future* revenues. Lastly, replacing capital typically involves deterministic adjustment costs that are proportional to the stock of capital (see, e.g., Zhang 2005; Garlappi and Song 2017; Equation (13)). In contrast, replacing a customer involves no such adjustment costs, but requires the firm to pay a stochastic cost that is related to the difficulty of replacing customers.

3.3 Firm's problem

The firm takes the SDF used to value cash flows in period $t+1$, $M_{t,t+1}$, as given. Motivated by the evidence in Section 2.2, we specify the SDF as a function of the two aggregate shocks in the economy:

$$M_{t,t+1} = \frac{\beta \exp\left(-\gamma_{a,t}\sigma_a\varepsilon^a_{t+1} - SGN \cdot \gamma_f\sigma_f\varepsilon^f_{t+1}\right)}{\mathbb{E}_t\left[\exp\left(-\gamma_{a,t}\sigma_a\varepsilon^a_{t+1} - SGN \cdot \gamma_f\sigma_f\varepsilon^f_{t+1}\right)\right]}. \tag{18}$$

Here, $\gamma_f > 0$ 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. In particular, the ε^f_{t+1} shock that governs the search costs (e.g., via a decrease in customer entry or an increase supplier competition as shown empirically in Section 2.1) raises the marginal utility of investors and should have a negative price of risk.

The market price of risk of aggregate productivity shocks, $\gamma_{a,t}$, is positive and time-varying:

$$\gamma_{a,t} = \exp\left(\gamma_a \Delta a_t\right), \tag{19}$$

where $\Delta a_t = \log(A_t/A_{t-1})$. When $\gamma_a < 0$, the price of risk for aggregate productivity shocks varies countercyclically. The mechanism underlying this well-documented countercyclical variation can reflect time-varying risk aversion (Campbell and Cochrane 1999) or countercyclical stochastic volatility. Note that we normalize 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

$$\hat{D}_{it} = Y_t\left(1 - r_{it+1}\right) - \xi K_{it} - I_{it} - \phi\left(I_{it}, K_{it}\right)K_{it}. \tag{20}$$

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.[14] If the customer from the previous period defaults at the beginning of period t, then

$$D_{it} = \hat{D}_{it} - f_{t-1} A_{t-1}. \tag{21}$$

Otherwise, the firm recoups the trade receivables extended during period $t-1$ and

$$D_{it} = \hat{D}_{it} + Y_{it-1} r_{it}. \tag{22}$$

We define $V(K_{it}, C_{it}, A_t, f_t, R_{it-1}, \iota_{it})$ as the cum-dividend market value of firm i, where $R_{it-1} = r_{it} Y_{it-1}$ is the amount of trade receivables 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 trade credit policies to maximize its market value

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

Section IA.5 of the Internet Appendix describes how to detrend the model and the procedures employed to solve the model via value function iteration.

4 Explaining the Facts: Theory

4.1 Calibration

Table 10 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.

[14] Our definition of dividends here implicitly assumes that firms are all-equity financed. Since firms in the data are financed with both equity and debt, we follow Boldrin, Christiano, and Fisher (2001) and Papanikolaou (2011) and scale all model-implied returns by a factor of 5/3 to tighten the link between the model and the data.

4.1.1 Parameter choice.

Technology. We set the drift, μ_a, and volatility, σ_a, of aggregate productivity to match the mean and volatility of aggregate output. The parameter σ_c governs cross-sectional heterogeneity in the quality of potential counterparties and drives the idiosyncratic volatility of output in the model. We set this parameter to 0.6 to target a firm-level volatility of sales growth of about 30% per annum.

Because receivables in the model hedge firms from having to pay customer search and rematching costs, the parameters governing this cost are directly linked to the moments of firm-level R/S ratios. There is a monotonic relation between f_0 and the average R/S ratio in our model. We set the mean (volatility) of the search cost shocks f_0 (σ_f) to target the mean (volatility) of firm-level R/S of 19.5% (5%). These choices of f_0 and σ_f do not directly target the model-implied counterparty premium.

Capital. We set the depreciation rate (δ) to 0.08 and capital's 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 ratios 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 3.40, 3.90 and 4.06 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. Specifically, while $\underline{p}$ ($\overline{p}$) is tightly related to the duration of the longest (shortest) model-implied link, the convexity parameter λ governs medium link duration. The choice of these three parameters is also quantitatively consistent with the negative empirical relation between R/S and the probability of links breaking in Table 5. The parameter ν governs the extent to which customer defaults are systematic and is set to match the correlation between the logarithmic growth rate of aggregate productivity and the logarithmic change in the average doubtful receivables-to-sales ratio to the data. Here, we measure the model-implied doubtful R/S ratio as $r_{i,t+1}$ multiplied by the expected default probability of $\Gamma(r_{i,t+1})$, or $r_{i,t+1}\Gamma(r_{i,t+1})$.

SDF. We set the time discount rate β to target a constant risk free rate of 2.1% per annum. We set the two market prices of risk, γ_a and γ_f, such that the mean (volatility) of the model-implied equity premium is 8.7% (15.8%) per annum, as in the data. Here, γ_a mainly affects the volatility of the equity premium as it induces time-varying prices of risk, while γ_f mainly affects the level of the equity premium. The sign of the market price of risk of counterparty shocks is negative ($SGN = -1$), consistent with the evidence in Tables 3 and 7.

4.1.2 Model fit for aggregate and firm-level moments.

Panel A of Table 11 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, close to the data. The model-implied Sharpe ratio is 0.54 in both the model and the data. While not directly targeted, the autocorrelation of aggregate output in the model is 0.32, close to its empirical counterpart of 0.23. In both the model and the data, the fraction of doubtful receivables-to-sales increases when aggregate productivity decreases. The correlation between the growth rates of these two measures is about -0.1.

Panel B of Table 11 shows both model-implied and empirical moments for firm-level quantities. The firm-level mean of R/S is 19.5% (19.48%) per annum in the data (model), while the firm-level volatility of R/S is about 5.5% (4.6%) 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 smaller in the model than in 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 29.9% (27.5%) in the model (data), while the latter is 10.6% (10.8%) in the model (data).

4.2 Facts 1 and 2: Model versus data

Our empirical analysis yields two main facts: high R/S firms (1) have considerably *lower* risk premiums and (2) maintain *longer* duration links with their customers. Panels C and D of Table 11 show that the model replicates both of these facts. We show this by using model-simulated data to sort firms into portfolios based on their R/S ratios. Our model-implied results use an identical empirical procedure to that described in Section 1, such that the low (high) portfolio includes firms in the bottom (top) decile of the cross-sectional distribution of R/S as of the formation period.

The model-implied spread between the returns of low and high R/S firms is about 7.6% per annum in the data versus 5.8% 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. Moreover, the expected duration of supplier-customer links for low (high) R/S firms is 3.46 (4.06) years in the model. This is very close to the estimate of 3.40 (4.06) years. We elaborate on the logic and the economic mechanism for these results in Section 4.4.

Importantly, all firms in the model are assumed to be suppliers that operate within a given layer of the production network (i.e., all suppliers have the same distance to final 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., controlling for suppliers' vertical positions in supply chains), averaged across all production layers. Section IA.4.1 of the Internet Appendix shows that the counterparty premium exists *within* both the downstream and the upstream production layers, with an average magnitude of 6% per annum *across* the production layers, in line with the quantitative model.

4.3 Aggregate trade credit and the counterparty premium

We use model-simulated data to examine whether the aggregate amount of trade credit can explain the counterparty premium, as demonstrated empirically in Section 2.2. We mimic the empirical analysis by computing the average receivables-to-sales ratio across all firms at time t that we denote by $\overline{R/S}_t$. To explain the motivation behind the use of $\overline{R/S}_t$ as a macroeconomic observable for underlying customer-search costs, we check its model-implied correlations with the counterparty search cost f_t and with aggregate TFP growth, Δa_t. These model-implied correlations are 0.99 and 0.01, respectively. Likewise, the correlation between innovations to $\overline{R/S}_t$, measured by its log first difference, and f_t (Δa_t) is 0.98 (approximately zero). This result provides additional theoretical support to prediction 1 of Section 2.1 that the aggregate motive for extending trade credit is tightly linked to the costs of searching for customers. Namely, $\overline{R/S}_t$ innovations are a good proxy for customer-search costs shocks (i.e., ε^f_{t+1}).

We then repeat the GMM analysis from Section 2.2 using model-simulated data. We posit that the SDF is identical to Equation (6), where $MKRTF_t$ is the value-weighted excess market return and $MACRO_t$ is the $\overline{R/S}_t$ innovation. As in Section 2.2, we use the returns of 10 portfolios sorted on R/S as test assets. We repeat the GMM estimation of Equation (7) 100 times using finite samples and report the median factor loadings for the market return (b_{MKTRF}) and aggregate trade credit innovation ($b_{\overline{R/S}}$), as well as the median pricing error (α) for the low-minus-high R/S portfolio (i.e., the counterparty premium) in panel A of Table 12. We also report the 90% confidence interval for each statistic across the simulations. Similar to the empirical results, the model-implied price of risk for the market return is positive, while the price of risk for $\overline{R/S}$ innovations is negative. In particular, the median value of $b_{\overline{R/S}}$ is -5.91 in the model versus -6.91 in the data (see panel C of Table 7).[15] The negative value of $b_{\overline{R/S}}$ indicates that states with more trade credit extension correspond to higher marginal utility states in which the search cost for new customers (f_t) is higher.

The median pricing error for the counterparty premium is 21 basis points and statistically insignificant across all simulations. Importantly, including $\overline{R/S}$ innovations in the SDF is essential to explain the R/S spread. When we repeat the GMM analysis using only the market factor in the SDF, b_{MKTRF} remains positive but the median pricing error for the counterparty premium turns strictly positive: the lower bound of its model-implied confidence interval exceeds 2%. This echoes the leftmost column of Table 7, showing that the CAPM fails to explain the counterparty premium in the data.

Panel B of Table 12 reports the model-implied covariance between $\overline{R/S}$ innovations and the stock returns of the low (decile 1), medium (decile 5), and high (decile 10) R/S-sorted portfolios. Similar to the data, the absolute values of the covariances decrease monotonically from the low to the high R/S portfolio. The covariance of the medium R/S portfolio's returns with $\overline{R/S}$ innovations is -0.28 in the model compared to -0.31 in the data (see panel B of Table 7). The model-implied counterparty premium has a covariance of -0.27 with the innovations to aggregate trade credit. In comparison, panel B of Table 7 shows that the empirical counterpart of this covariance is -0.77, with a confidence

[15] Following Giglio, Kelly and Xiu (2021), among others, we convert the SDF loading $b_{\overline{R/S}}$ into a factor risk premium $\lambda_{\overline{R/S}}$ using the covariance matrix of the two shocks. In the model, $\lambda_{\overline{R/S}} = -4.25$ (in percentage points) with a 95% confidence interval of $[-5.41, -3.04]$. Similarly, based on the estimates for $b_{\overline{R/S}}$ in Table 7, and the empirical covariance matrix, we obtain that $\lambda_{\overline{R/S}} = -4.02$ in the data, with a confidence interval of $[-4.86, -3.17]$. Note that the confidence intervals of $\lambda_{\overline{R/S}}$ in the model and in the data overlap.

interval of $[-1.35, -0.18]$. While the covariance in the model is somewhat smaller than the data, this value falls well within the empirical confidence interval.

Panel C of Table 12 reports the model-implied covariance between $\overline{R/S}$ innovations and the cash flows of R/S-sorted portfolios. We measure the model-implied cash flows using the average dividends of each portfolio normalized by the average sales of each portfolio for stationarity. The cash flow sensitivity is computed by estimating Equation (8) using model-simulated data. The low, medium, and high R/S portfolios have a median cash flow exposure of -0.55, -0.02, and 0.03 to $\overline{R/S}$ innovations across the finite-sample simulations, respectively. This closely mirrors the empirical counterparts in panel D of Table 7. Specifically, the low R/S portfolio has the most negative exposure to changes in customer-search costs, as proxied by changes in $\overline{R/S}$.[16]

4.4 Inspecting the mechanism

Idiosyncratic motive for extending trade credit. The left panel of Figure 2 shows the model-implied policy for a firm extending trade credit as a function of its customer's underlying quality. The relation between R/S and customer quality is positive and monotonic. The higher the quality of the customer, the greater the firm's incentive to keep the customer going forward. As such, the hedge that firms 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 customers with insufficient quality. This is because the supplier hopes a liquidity shock will cause its current customer to default, allowing the firm to draw a new customer from the pool next period. 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 the firm-specific component of R/S can proxy for the underlying (unobserved) quality of the customer.

[16] The cash flow exposure of the low-minus-high R/S portfolio is -0.57 within the model. This falls within the confidence interval for this quantity in the data. Panel D of Table 7 shows that the empirical equivalent is about -0.3 with a 90% confidence interval of [-0.09,-0.60].

This is qualitatively consistent with the empirical findings of Prediction 4 in Section 2.4.

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 R/S 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 probability of default. Thus, low R/S firms are more likely to search for a new customer next period. While all firms' valuations are negatively affected by shocks that increase the search cost f_t, low R/S firms are more adversely affected by these shocks as these firms are more likely to pay the cost associated with searching. This exposure pattern is consistent with panel B of Table 12 when the search-cost shocks are proxied using $\overline{R/S}$ innovations. Collectively, this implies $\beta_f^{R/S=LOW} < \beta_f^{R/S=HIGH} < 0$, where $\beta_f^j = \frac{1}{\sigma_f} \frac{\partial V_{j,t}}{\partial \varepsilon_t^f}$. The contribution of the search-cost shock to the counterparty premium is given by $\left(\beta_f^{R/S=LOW} - \beta_f^{R/S=HIGH}\right) SGN \cdot \gamma_f \sigma_f^2$. Since shocks to the cost of searching for and matching with new customers are negatively priced in the cross-section (recall panel A of Table 12), these shocks contribute positively to the spread.

Contribution of $\boldsymbol{\varepsilon^a}$ shocks. The contribution of aggregate productivity shocks to the counterparty premium is given by $\left(\beta_a^{R/S=LOW} - \beta_a^{R/S=HIGH}\right) \gamma_{a,t} \sigma_a^2$, where $\beta_a^j = \frac{1}{\sigma_a} \frac{\partial V_{j,t}}{\partial \varepsilon_t^a}$. The relative exposure of low versus high R/S firms to ε^a shocks depends on the balance between two forces.

On one hand, Equation (14) suggests that customer defaults occur more frequently when aggregate productivity is lower. Thus, firms with high R/S have more to lose from customer defaults than low R/S firms, precisely in bad states. This makes the extension of trade credit costly in the systematic sense and increases the exposure of high R/S firms to aggregate productivity shocks.

On the other hand, firms with low R/S are endogenously matched with lower-quality customers. Thus, holding 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 (10)). Since the fixed cost ξ does not scale proportionately with either sales or aggregate productivity, the fixed cost creates operating leverage. Given their lower sales, low R/S firms have more operating leverage than high R/S firms. Consequently, this operating leverage effect increases the exposure of low R/S firms to aggregate productivity shocks.

Because of these conflicting channels, aggregate productivity shocks have an a priori ambiguous effect on the counterparty premium. In what follows, we perform a sensitivity analysis to examine how each priced shock and other key model parameters affect the counterparty premium.

The role of priced counterparty shocks (γ_f). Almost the entire R/S spread is driven by the shocks to customer-search costs (ε^f). Row 3 of Table 13 shows that if the market price of risk of these counterparty shocks (γ_f) is zero, then the R/S spread is still positive but small in magnitude. The fact that the spread falls sharply suggests that about 99% of the counterparty premium in the model is explained by the counterparty shocks. The quantitative effect of systematic defaults offsets with the operating leverage effect and makes the contribution of aggregate productivity shocks negligible. Relatedly, row 4 shows that the counterparty premium turns negative when the sign of the market price of risk of the counterparty shocks is counterfactually switched to positive ($SGN = 1$). In this case, counterparty shocks negatively contribute to the R/S spread as $\beta_f^{R/S=LOW} < \beta_f^{R/S=HIGH} < 0$.

The role of average customer-search costs (f_0). Rows 5 and 6 of Table 13 perturb f_0 upward and downward from its benchmark value, respectively. Since f_0 is calibrated to match the average firm-level R/S ratio to the data, a higher value of f_0 increases the common incentive to extend trade credit since there is a greater benefit in hedging a larger search cost. Increasing (decreasing) the benchmark value of f_0 results in an average R/S ratio that is higher (lower) than its empirical counterpart of 19.50%. At the same time, a higher (lower) value of f_0 amplifies (attenuates) the R/S spread. This is consistent with ε^f shocks serving as the primary driver of the counterparty premium. Changing f_0 has a negligible effect on the volatility of investment, sales growth, and GDP growth.

The role of systematic defaults (ν). A negative value of ν suggests that the probability of customer default rises as aggregate productivity falls. The prospect of losing trade credit in low productivity states rises as ν turns more negative and, all else equal, this increases the risk of high R/S firms relative to the risk of low R/S firms. For example, row 7 of Table 13 increases the value of ν (in absolute terms) from its benchmark value. Accordingly, the counterparty premium falls from 5.8% to 4.4%. At the same time, the correlation between the model-implied growth rates of aggregate productivity and average doubtful receivables-to-sales becomes -0.15, a quantity that is 50% larger than its empirical counterpart in absolute terms.

Similarly, when $\nu = 0$, customer defaults in the model are completely idiosyncratic. This lowers the risk involved in extending trade credit and, ceteris paribus, further decreases the risk of high R/S

firms compared to that of low R/S firms. Row 8 of Table 13 shows that the tradeoff between the risks associated with customer turnover and customer default is nontrivial. Without systematic defaults, the R/S spread rises by 4.4% relative to its benchmark value of 5.8%. This sizable amplifications of the spread comes at the cost of the model featuring a counterfactual zero correlation between doubtful receivables and productivity. The R/S spread remains positive for all plausible values of ν, in spite of the possibility of systematic customer defaults. This is consistent with Prediction 6 of Section 2.

The role of capital adjustment costs (b). The degree of capital adjustment costs is set to target the volatility of firm-level investment rates to the data. In the last row of Table 13 we search for a value of b such that the counterparty premium is as close to the data as possible. We find that increasing b to roughly two increases the R/S spread to 7.4%. When adjustment costs rise, productivity shocks are absorbed in the price of capital rather than investment. Because low R/S firms face lower idiosyncratic productivity, their disinvestment risk is larger which is amplified with greater capital frictions. However, the amplification in the R/S spread comes at the cost of lowering firm-level investment volatility to about 10%. Similarly, the R/S spread is somewhat smaller for a lower value of b, while investment's volatility is larger.

4.5 Model extensions

To maintain quantitative tractability, certain aspects of the data are modeled in reduced form. Yet, we discuss and when possible relax these assumptions in Section IA.4 of the Internet Appendix. First, we document that the model's implications are materially unchanged if suppliers are assumed to operate either downstream or upstream, or have multiple customers. The appendix also shows that the counterparty premium is amplified by introducing either the strategic termination of links or persistence in the quality of customers, but the premium is somewhat attenuated by introducing customer-independent idiosyncratic productivity shocks. Nonetheless, in all alterations, the model-implied counterparty premium is well within the data's confidence interval.

5 Conclusion

We examine the implications of trade credit for asset prices, network links, and customer-search costs. We document several novel facts. First, low R/S firms earn a higher risk premium. We label the spread between the returns of low and high R/S firms the "counterparty premium." This premium is unexplained by common asset pricing factors and characteristics, and a new asset pricing factor based on the premium is priced negatively in stock returns. Second, R/S is an economically important predictor of the average duration of supplier-customers links. Specifically, suppliers that extend more (less) trade credit to their customers have longer (shorter) relationships with their customers. Higher R/S is also associated with a reduced probability of a supplier-customer link breaking.

We construct a production-based model with trade credit to quantitatively tie the former facts together. Suppliers are matched with customers of heterogeneous quality, but customers may experience shocks that terminate these relations (e.g., default shocks). Suppliers can extend trade credit to provide liquidity to their customers but face a tradeoff in doing so. On one hand, the trade credit could be lost. On the other hand, lower provision of trade credit increases the probability of customer turnover. Both scenarios are risky: customer defaults occur more frequently in downturns, and supplier must pay a systematic search cost to rematch with a new customers. The model quantitatively matches the counterparty premium to the data. Low R/S firms are endogenously matched with worse customers and are more likely to search for a new customer next period. These low R/S firms have a greater exposure to systematic shocks that govern the cost of searching for a new counterparty. The model also replicates the fact that low R/S firms have lower duration links with their counterparties.

We establish other novel findings in support of this risk-based mechanism. Notably, we show that the aggregate amount of trade credit in the economy serves as a proxy for the potentially unobserved customer-search costs. Indeed, this macro variable theoretically increases with shocks that raise search costs, and empirically increases when the anticipated pool of new firms shrinks or as competition between suppliers intensifies. The returns of low R/S firms are more negatively exposed to innovations in this search-cost proxy that carries a negative market price of risk. Consequently, this proxy renders the pricing error of the counterparty premium insignificant in both the model and the data. Moreover, we empirically and theoretically demonstrate that firm-level trade credit provision serves as an observable proxy for customer quality, and that customer search and replacement reduces firms' cash flows. Finally, firms that maintain shorter duration links with their customers have a higher risk premium.

In all, the empirical and theoretical evidence suggests that trade credit contains important information about both micro- and macro-level risks and the dynamics of links in the production network. Replacing a customer is costly. Micro-level trade credit provides a mechanism that induces high-quality customers to maintain their relations with the firm. This boosts firms' profits, and hedges against potential "breakups" with good customers. Macro-level trade credit provides a gauge for how costly it is to replace customers. An interesting avenue for future studies is to more broadly examine the connection between credit lines and link duration in the context of financial networks involving banks and other institutions.

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Tables and Figures

Table 1: Portfolios sorted on R/S

The table reports the average monthly returns of portfolios sorted on the trade receivables to sales (R/S) ratio and 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 ratios below (above) the 10th (90th) percentile of the cross-sectional distribution of R/S ratios from fiscal year ending in calendar year $t-1$. Panel A reports the returns of portfolios constructed using the R/S ratio defined in Equation (1), whereas panel B reports the returns of portfolios constructed using the industry-adjusted R/S ratio, denoted by R/S^{IA}. This industry adjustment at time t is implemented by (a) assigning each firm to its Fama-French 30 industry group and (b) subtracting each industry's time-t cross-sectional median R/S ratio from each firm's R/S ratio. Both panels report value-weighted returns. Mean refers to the average monthly return and SD denotes the standard deviation of monthly returns. Parentheses report Newey and West (1987) robust t-statistics. All portfolios are formed at the end of each June from 1978 to 2020 and are rebalanced annually. Thus, portfolio returns span July 1978 to December 2020.

	A. R/S		*B. R/S^{IA}*	
Portfolio	Mean	SD	Mean	SD
Low R/S	1.253	4.868	1.349	5.479
Medium	1.114	4.590	1.096	4.533
High R/S	0.617	5.987	0.744	5.868
Spread	0.636	4.014	0.605	3.720
(L-H)	(3.28)		(4.01)	

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 on 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), whereas MOM is the momentum factor of Carhart (1997). Profit. and Invest. correspond to the RMW and CMA factors (ROE and I/A factors) of the Fama and French (2015) five-factor (Hou et al. (2021) q^5-factor) model, while EG represents the expected growth factor from the q^5 model. Values in parentheses report Newey and West (1987) robust t-statistics. Returns span July 1978 to December 2020.

	CAPM	FF3F	FF4F	FF5F	q^5
MKTRF	-0.320	-0.285	-0.261	-0.244	-0.233
	(-6.29)	(-5.49)	(-4.86)	(-4.92)	(-4.22)
SMB		-0.100	-0.104	0.011	0.034
		(-1.35)	(-1.36)	(0.14)	(0.46)
HML		0.119	0.169	0.040	
		(0.12)	(0.17)	(0.45)	
MOM			0.118		
			(2.02)		
Profit.				0.399	0.346
				(3.81)	(2.72)
Invest.				0.103	0.254
				(0.90)	(2.61)
EG					0.145
					(0.15)
α	0.863	0.833	0.741	0.643	0.533
	(4.68)	(4.65)	(4.24)	(3.76)	(3.19)

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 (CPR) 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. 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 made using the value-weighted returns of the following three sets of test assets: (1) 25 size and book-to-market portfolios, (2) the first set of test assets plus the 49 Fama-French industry portfolios, and (3) the second set of test assets plus 10 portfolios sorted on each of investment, profitability, momentum, market betas, stock issuance, accruals, variance, and residual variance. The t-statistic associated with each risk factor loading is reported in parentheses and the mean absolute error (MAE) associated with each estimation procedure is reported in the bottom row of each panel. Monthly data spanning July 1978 to December 2020 is used to estimate each model.

	25 portfolios		74 portfolios		154 portfolios	
A. CAPM plus the counterparty risk factor						
	CAPM	+CPR	CAPM	+CPR	CAPM	+CPR
b_{MKTRF}	3.662	8.369	3.557	5.260	3.376	6.181
	(3.36)	(4.74)	(3.35)	(4.62)	(3.35)	(6.14)
b_{CPR}		-14.167		-5.199		-8.360
		(-3.35)		(-3.57)		(-7.09)
MAE	0.706	0.585	0.886	0.793	0.923	0.744
B. FF3F plus the counterparty risk factor						
	25 portfolios		74 portfolios		154 portfolios	
	FF3F	+CPR	FF3F	+CPR	FF3F	+CPR
b_{MKTRF}	3.763	9.352	4.253	5.408	4.436	6.161
	(3.24)	(4.83)	(3.91)	(4.67)	(4.40)	(5.98)
b_{SMB}	0.542	2.874	-2.384	-1.263	-3.796	-1.940
	(0.34)	(1.50)	(-1.51)	(-0.79)	(-2.61)	(-1.31)
b_{HML}	3.622	0.539	0.318	-0.483	1.087	-0.200
	(2.11)	(0.25)	(0.19)	(-0.29)	(0.67)	(-0.12)
b_{CPR}		-20.147		-4.693		-6.940
		(-4.01)		(-3.16)		(-5.54)
MAE	0.617	0.505	0.879	0.801	0.804	0.717

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 2020, as the FactSet Revere database is only available beginning in April 2003. Section IA.1 of the Internet Appendix provides details about the construction of each variable. 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	0.30	0.55	0.50	-0.20	(-1.27)
Upstreamness	1.76	2.73	3.06	-1.30	(-11.92)
HHI (Customer)	0.04	0.05	0.05	-0.00	(-0.42)
IVOL (Customer)	1.73	1.51	1.50	0.23	(1.12)
Loan spread (Customer)	1.84	1.90	1.87	-0.03	(-0.08)
Secured debt (Customer)	0.43	0.39	0.30	0.13	(0.92)
Debt covenants (Customer)	0.60	0.55	0.41	0.18	(1.44)
Duration	40.88	47.18	48.69	-7.81	(-3.19)

Table 5: Predicting the length of supplier-customer links

The table reports the results of Fama-MacBeth regressions that use industry-adjusted supplier-level characteristics to predict the average duration, D_t, 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 1.3.2. Our measure of link duration is either (1) the average future duration of each supplier's links with its customers (measured in months in panel A) or (2) an indicator variable Break that is equal to one in the situation in which at least half or more of a supplier's customers at time t are no longer active customers in 4 years' time. Finally, Newey and West (1987) robust t-statistics are reported in parentheses and each supplier-level characteristic is standardized by dividing the characteristic by its unconditional standard deviation. The table also reports the maximal share of D_t explained by the supplier-level characteristics. The time period for the analysis ranges from June 2003 to June 2020.

	A. Future duration		*B. $Pr(Break = 1)$*	
Constant	44.63	44.57	0.63	0.62
	(6.90)	(6.91)	(20.79)	(21.64)
R/S	4.15	4.09	-0.09	-0.09
	(3.01)	(3.07)	(-4.39)	(-4.15)
ln(ME)	0.14	0.35	0.03	0.04
	(0.44)	(0.91)	(4.94)	(6.27)
ln(B/M)	-0.12	-0.08	0.01	0.01
	(-0.35)	(-0.25)	(0.44)	(0.60)
I/K	-0.32	-0.35	-0.00	-0.00
	(-0.48)	(-0.52)	(-0.40)	(-0.31)
ROA	1.25	1.22	-0.02	-0.02
	(3.92)	(3.92)	(-3.59)	(-3.91)
Lagged duration	5.13	5.14	-0.09	-0.09
	(5.49)	(5.45)	(-6.65)	(-5.91)
Number of customers		-0.66		-0.02
		(-2.44)		(-2.39)
R^2 (%)	14.25	14.26	10.18	11.22

Table 6: Aggregate trade credit extension and customer search costs

The table reports the results of the projection $\overline{R/S}_t = \rho_0 + \rho_{SearchCost}SearchCost_t + \rho_{TFP}TFP_t + \varepsilon_t$, where $\overline{R/S}_t$ is the aggregate receivables-to-sales ratio at time t, $SearchCost_t$ is a macroeconomic variable that is associated with an increase in customer-search costs, and TFP_t is the utilization-adjusted total factor productivity from Fernald (2012). The first measure of customer search costs is "DeathMinusBirth," which is the expected difference between the death and birth rate of establishments from the BLS. This expected death-minus-birth rate of establishments is obtained from the fitted value of a regression of the death-minus-birth rate at time $t+1$ on a constant, the current death-minus-birth rate of establishments at time t, and other time-t predictors including the corporate credit spread and the excess returns of the market portfolio. The second measure of customer search costs, "RelativeCompetition," captures the concentration of customers relative to suppliers, and is constructed in three steps. First, in each quarter, each firm in the sample is denoted a customer (supplier) firm if its upstreamness score from Gofman, Segal, and Wu (2020) is below (above) the 30th (70th) percentile 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 period is annual from 1978 (1992) to 2020 for regressions including RelativeCompetition (DeathMinusBirths).

	(1)	(2)	(3)	(4)	(5)
DeathMinusBirths		0.37	0.43		
		(3.53)	(4.42)		
RelativeCompetition				0.56	0.54
				(3.41)	(3.35)
TFP	0.24		0.38		0.19
	(1.13)		(2.48)		(1.13)
$\bar{R}^2$ (%)	3.27	10.20	21.61	29.63	31.46

Table 7: Pricing R/S-sorted portfolios using macroeconomic variables

The table reports statistics related to the ability of different macroeconomic shocks to price the R/S-sorted portfolios. We posit that the SDF is given by Equation (6) and is driven by the market's excess return ($MKTRF_t$) and an additional macroeconomic shock ($MACRO_t$), including (a) innovations to the aggregate receivables-to-sales ratio ($\overline{R/S}$), measured by its log first difference, (b) innovations to the utilization-adjusted TFP from Fernald (2012) (TFP), measured by its log first difference, (c) the corporate default spread (DEF), (d) macroeconomic uncertainty from Jurado, Ludvigson, and Ng (2015) (UNC), (e) investment-specific technology shocks proposed by Papanikolaou (2011) (IST), (f) intermediary capital from He, Kelly, and Manela (2017), and (g) the equity cost issuance shock from Belo, Lin, and Yang (2019) (ECS). We use GMM to estimate Equation (7) using the 10 R/S-sorted portfolios, constructed following the procedure in Section 1.2, as test assets. Panel A reports model-implied pricing errors (α) associated with the GMM procedure, and panel B reports the covariance between portfolio returns and the macroeconomic shocks $MACRO_t$. The leftmost column in panel A, entitled $MKTRF$, omit $MACRO_t$ from the SDF, such that the SDF includes only the market's excess returns. Panels C and D focus on aggregate trade credit as the macroeconomic variable of interest. Specifically, panel C reports the market price of risk associated with $MKTRF_t$ and $\overline{R/S}$ innovations when the test assets are either (a) the 10 R/S-sorted portfolios or (b) a broader set of test assets that features the five Fama-French industry portfolios, six portfolios sorted on size and book-to-market, six portfolios sorted on size and profitability, and six portfolios sorted on size and investment. Finally, panel D reports the sensitivity of the cash flows underlying the R/S-sorted portfolios to variations in aggregate trade credit. The sensitivity of each portfolio corresponds to β_2 from Equation (8). Cash flows are measured using (a) divided growth, which is constructed by compounding the difference between the total returns and the returns excluding dividends of each portfolio, (b) the average dividends per share of each portfolio, or (c) the average profitability of each portfolio, measured using EBIT-to-assets. Each of these cash flow measures are industry-adjusted. The data underlying this analysis are annual and spans 1978 to 2020. Newey and West (1987) t-statistics are reported in parentheses.

A. Model-implied alphas

	MKTRF	$\overline{R/S}$	TFP	DEF	UNC	IST	INT	ECS
Low R/S (L)	9.08	-0.95	9.08	8.40	6.51	-2.57	6.73	8.59
Medium R/S	-4.03	1.55	5.34	8.84	4.94	-1.20	4.77	5.44
High R/S (H)	-11.53	-0.11	1.63	2.84	-1.36	-0.53	0.62	-2.19
Spread	9.97	-0.84	7.44	5.55	7.87	-2.04	6.11	10.78
(L-H)	(4.02)	(-0.37)	(3.18)	(2.11)	(2.22)	(-1.97)	(2.04)	(3.96)

B. Covariance with macroeconomic variable

	$\overline{R/S}$	TFP	DEF	UNC	IST	INT	ECS
Low R/S (L)	-0.65	-3.12	-0.88	0.12	0.26	-2.93	26.47
Medium R/S	-0.31	-5.75	-2.18	-0.01	0.20	-5.01	51.56
High R/S (H)	0.12	-0.38	-3.12	-0.25	0.06	-17.71	27.54
Spread	-0.77	-2.75	2.24	0.37	0.20	14.79	-1.07
(L-H)	(-2.65)	(-0.66)	(1.59)	(0.81)	(3.01)	(1.18)	(-0.04)

C. Market prices of risk

	R/S portfolios		Broader test assets	
b_{MKTRF}	4.38	1.59	4.69	1.41
	(4.47)	(1.90)	(14.20)	(4.41)
$b_{\overline{R/S}}$		-14.50		-6.91
		(-4.70)		(-9.21)
MAE	5.60	1.35	7.82	1.09

D. Cash flow sensitivity

	Div. growth		Div. per share		EBIT / AT	
Portfolio	β	$t(\beta)$	β	$t(\beta)$	β	$t(\beta)$
Low R/S (L)	-0.34	(-5.38)	-11.17	(-9.05)	-0.06	(-0.47)
Medium R/S	-0.29	(-4.04)	-9.06	(-6.16)	0.51	(3.95)
High R/S (H)	-0.01	(-0.17)	1.98	(0.89)	0.29	(2.20)
Spread (L-H)	-0.33	(-4.94)	-13.16	(-5.09)	-0.35	(-2.70)

Table 8: Searching for new customers and profit margins

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

Characteristic	$\mathbb{I}_{NewCustomers} = 0$	$\mathbb{I}_{NewCustomers} = 1$	Difference	t(Diff.)
Div. per share	0.26	0.17	0.09	(10.70)
Profit margin	0.06	-0.22	0.27	(6.80)
ROA (%)	1.72	0.98	0.74	(13.88)
Operating costs	-0.02	0.01	-0.03	(-8.74)
TFP	0.15	0.05	0.10	(9.65)

Table 9: Portfolios sorted on link duration: Returns, pricing errors, and risk exposures

The table reports the average monthly returns of link duration (DUR) sorted portfolios and their pricing when we estimate Equation (7) using innovations to aggregate trade credit as $MACRO_t$. At the end of each month from June 2003 onward, the cross-section of firms is sorted into three portfolios based on the $10th$ and $90th$ percentiles of the cross-sectional distribution of link duration at the end of the previous month. As such, portfolio returns span July 2003 to December 2020. Panel A reports the returns of portfolios constructed using link duration as a sorting variable, and panel B reports the returns of portfolios sorted on industry-adjusted link duration, denoted by Duration^{IA}. This industry adjustment is implemented by (a) assigning each firm to its Fama-French 30 industry group and (b) subtracting each industry's cross-sectional median link-duration from each firm's link duration. Here, Mean refers to the average value-weighted monthly return, and SD denotes the standard deviation of monthly returns. Panels C and D report the results of estimating the moment condition denoted by Equation (7) using GMM. Here, the macroeconomic shocks $MACRO_t$ are innovations to the aggregate receivables-to-sales ratio ($\overline{R/S}$), as measured by its log first difference. The test assets are the 10 duration-sorted portfolios that are constructed following the procedure outlined above. Panel C shows the model-implied pricing errors associated with the GMM procedure, and panel D shows the covariance of each portfolio returns with the macroeconomic shocks. The data underlying this GMM analysis is annual and spans 2003 to 2020. Parentheses in each panel report Newey and West (1987) robust t-statistics.

	A. Duration portfolio returns		*B. Duration*^{IA} portfolio returns		*C. Pricing errors* implied by $\overline{R/S}$		*D. Covariance* with $\overline{R/S}$	
Portfolio	Mean	SD	Mean	SD	α	$t(\alpha)$	Cov.	t(Cov.)
Low DUR	2.011	4.625	1.494	4.831	0.49	(0.47)	-0.02	(-2.42)
Medium	1.038	4.060	1.054	4.050	0.74	(1.35)	-0.00	(-0.39)
High DUR	1.039	4.257	1.004	4.502	0.83	(1.39)	-0.01	(-1.12)
Spread	0.972	2.744	0.490	2.483	-0.34	(-0.55)	-0.02	(-2.52)
(L-H)	(4.61)		(3.05)					

Table 10: 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
A. Technology			*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	0.49	Average matching cost	ξ	2.0	Fixed operating cost
σ_f	0.1	Matching cost volatility			
C. Liquidity shock probability			*D. SDF*		
$\overline{p}$	0.37	Pr(Shock if R/S=0)	β	0.979	Time discount factor
$\underline{p}$	0.24	Pr(Shock if R/S$\rightarrow \infty$)	γ_a	-84.1	Price of productivity shocks
λ	10	Convexity of shock function	γ_f	7.7	Magnitude of priced counterparty shocks
ν	-0.70	Cyclicality of liquidity shock	SGN	-1	Sign of priced counterparty shocks

Table 11: Model-implied moments against data

The table shows model-implied moments against their empirical counterparts. Panel A and B show moments related to aggregate and firm-level quantities, and panels C and D show the average returns and link durations of the R/S-sorted portfolios. All model-implied moments are based on model simulated data for 5,000 periods (years) and 1,000 firms. The model-implied sorting procedure in panels C and D is identical to the empirical strategy described in Section 1. That is, the low (high) R/S firms refers to the firms in the bottom (top) 10% of the cross-sectional distribution of the R/S ratio.

Statistic	Data	Model	Statistic	Data	Model
A. Aggregate moments			*B. Firm-level moments*		
Output growth:			*Receivables-to-sales (R/S):*		
Mean	2.51	1.97	Mean	19.50	19.48
Volatility	2	2.09	Volatility	5.55	4.58
Autocorrelation	0.23	0.32	Autocorrelation	0.45	0.42
Equity premium:			*Investment-to-capital (I/K):*		
Mean	8.78	8.67	Volatility	13.46	14.18
Volatility	15.98	15.82	Autocorrelation	0.33	0.24
Sharpe ratio	0.54	0.54	*Other:*		
Productivity and doubtful receivables growth:			Sales growth volatility	27.51	29.92
Correlation	-0.10	-0.09	Operating profits / sales volatility	10.80	10.63
C. R/S portfolio returns			*D. R/S portfolio duration*		
Low R/S	15.04	15.24	Low R/S	3.40	3.46
Medium R/S	13.37	11.75	Medium R/S	3.90	3.95
High R/S	7.40	9.40	High R/S	4.06	4.06
Spread	7.63	5.84	Spread	0.66	0.60

Table 12: Pricing R/S-sorted portfolios: Model-implied risk prices and exposures
The table shows the output implied by estimating the moment condition given in Equation (7) via GMM using model-simulated data. The macroeconomic shocks $MACRO_t$ are model-implied innovations to the aggregate receivables-to-sales ratio ($\overline{R/S}$), measured using the log first difference of the ratio. The test assets are 10 model-implied R/S-sorted portfolios, constructed using the same procedure used in the data. Panel A shows the model-implied market prices of risk for the market factor (b_{MKTRF}) and for innovations to the aggregate receivables-to-sales ratio ($b_{\overline{R/S}}$). The bottom row of the panel shows the pricing error (α) for the model-implied R/S-spread implied by this two-factor SDF. Panel B shows the exposure (covariance) of each model-implied R/S-sorted portfolio's returns with $\overline{R/S}$ innovations. Panel C reports the sensitivity of the cash flows of each R/S-sorted portfolio to $\overline{R/S}$. All moments are obtained from 100 finite-sample simulations of the economy, in which the analyses described in Section 2.2 are applied to the simulated data. Finally, values in brackets are the 90% confidence interval for each moment across the finite-sample simulations.

A. Prices of risk and α			*B. Risk exposures to $\overline{R/S}$*			*C. Cash flow sensitivity to $\Delta\overline{R/S}$*		
b_{MKTRF}	5.57	[4.66,7.14]	Low R/S (L)	-0.43	[-0.49,-0.37]	Low R/S (L)	-0.55	[-0.59, -0.49]
$b_{\overline{R/S}}$	-5.91	[-7.48,-4.29]	Medium R/S	-0.28	[-0.33,-0.23]	Medium R/S	-0.02	[-0.03, -0.02]
			High R/S (H)	-0.16	[-0.21,-0.12]	High R/S (H)	0.03	[0.00, 0.05]
α_{Spread}	0.21	[-0.07,0.53]	Spread	-0.27	[-0.30,-0.24]	Spread	-0.57	[-0.61, -0.54]

Table 13: Counterparty premium: Sensitivity analysis
The table shows the model-implied average firm-level R/S ratio (Mean(R/S)), investment volatility ($\sigma(I/K)$), sales growth volatility ($\sigma(\Delta\text{Sales})$), aggregate output growth volatility ($\sigma(\Delta\text{GDP})$), the correlation between aggregate productivity and the growth rate of doubtful receivables (ρ(TFP,Doubtful R/S)), and the counterparty premium across alternative calibrations of the model. Each alternative calibration is contrasted with both (a) the empirical quantity and (b) the benchmark value of each moment in the first two rows of the table.

Row	Moment	Mean(R/S)	$\sigma(I/K)$	$\sigma(\Delta\text{Sales})$	$\sigma(\Delta\text{GDP})$	ρ(TFP,Doubt R/S)	R/S spread
(1)	Data	19.50	13.46	27.51	2.00	-0.10	7.63
(2)	Benchmark [Calibration as in Table 10]	19.48	14.18	29.92	2.09	-0.09	5.84
(3)	$\gamma_f = 0$ [Counterparty shocks not priced]	19.30	13.35	30.02	2.09	-0.08	0.07
(4)	$SGN = 1$ [Counterparty shocks positively priced]	18.88	12.88	29.87	2.10	-0.07	-0.76
(5)	$f_0 \uparrow (f_0 = 0.50)$ [Higher avg. customer-search cost]	19.81	14.36	30.02	2.12	-0.09	6.61
(6)	$f_0 \downarrow (f_0 = 0.48)$ [Lower avg. customer-search cost]	19.20	14.33	30.11	2.11	-0.09	5.17
(7)	$\lvert\nu\rvert\uparrow (\nu = -1.2)$ [Customer default in worse states]	19.33	14.39	29.95	2.11	-0.15	4.39
(8)	$\lvert\nu\rvert\downarrow (\nu = 0.0)$ [Customer default idiosyncratic]	19.53	14.16	30.08	2.08	0.00	10.23
(9)	$b \uparrow (b = 2)$ [Higher capital adj. cost]	19.52	10.25	30.16	2.05	-0.08	7.38
(10)	$b \downarrow (b = 0.5)$ [Lower capital adj. cost]	19.29	17.74	30.14	2.17	-0.09	5.16

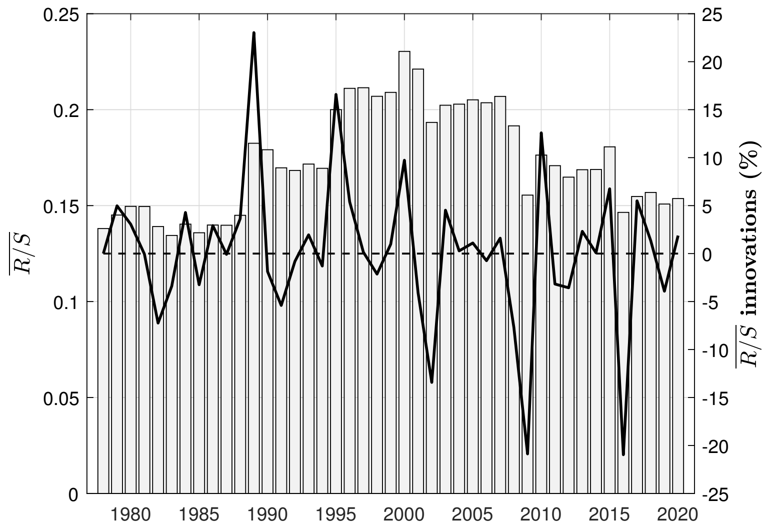

Figure 1: Innovations to the aggregate receivables-to-sales ratio
The figure shows the time series of the aggregate receivables-to-sales ratio $\overline{R/S}$ (gray bars) and its innovations (solid line). Innovations are computed as the logarithm of changes in the aggregate receivables-to-sales ratio. The sample spans from 1978 to 2020.

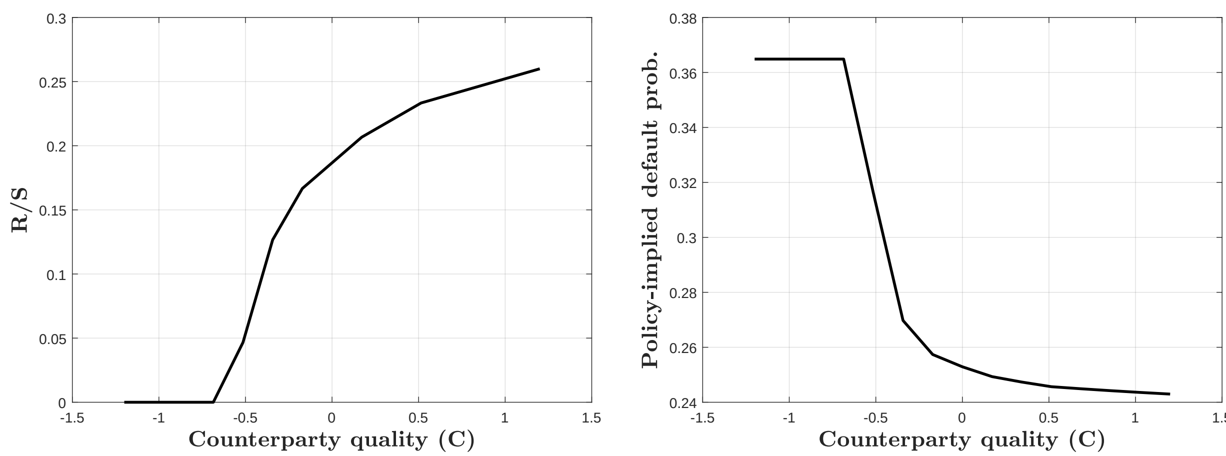

Figure 2: Model-implied policy functions
The left panel shows the model-implied policy for a firm's (supplier's) R/S (r) against different values of counterparty (customer) quality (C). The right panel shows the liquidity probability ($\Gamma(r)$ from Equation (14)) for the counterparty as implied by the R/S policy. Both policies are plotted when all other state variables are set to their stochastic steady-state values.