

Why Trade Credit?*

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Abstract

Why do virtually all firms—even the wealthiest—borrow from their suppliers? And why do financially constrained firms borrow substantially more? Data comprising 21 million invoices from 46 suppliers to 126,000 different corporate customers reveal that contracted trade credit duration is independent of the customer’s creditworthiness, and that overdue payments only account for a sixth of the variance in customers’ trade debt. We therefore hypothesize that financially constrained firms choose “buying” over “making” to increase their overall funding. As predicted, firms’ labor share is increasing in their credit rating, and within-industry purchases respond more strongly to financial constraints than do between-industry purchases.

Keywords: Trade credit; credit contracts; financial constraints; misallocation.

JEL: D24; L11; G32; G33.

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1 Introduction

Trade credit has long been an essential part of corporate funding. At its inception in 1782, the sole purpose of the Bank of North America, the first commercial bank in the U.S., was to produce liquidity by discounting trade bills. It actively resisted direct lending (Hammond, 1934). To this day, U.S. firms owe more money to their suppliers than to their banks (Figure 1, Panel A).¹ Yet, there is no generally accepted answer to the following simple question: Why do virtually all firms—even the wealthiest—borrow from their suppliers? For example, Murfin and Njoroge (2015) document that Wal-Mart borrows extensively from suppliers whose cost of funds appears much higher than Wal-Mart's.²

To say that all firms rely on trade credit is not to say that they do so to the same extent. There is a robust negative correlation between firms' creditworthiness and their accounts payable. Panel B of Figure 1 depicts the relationship for the large sample of Swedish firms that we consider here.

Arguably, this correlation constitutes *the* central regularity of trade credit research; see, e.g., Petersen and Rajan (1997). Most, if not all, interpretations of the regularity are variants of the following pecking-order theory: Firms of worse credit quality are forced to take more trade credit for the purpose of paying for inputs, as they have run out of other funds, such as bank credit. More precisely, financially constrained customers are hypothesized to pay their suppliers later, either by forgoing early-payment discounts, negotiating longer payment periods, or by delaying payment beyond the due date. Whatever the reason for the later payment, the customer will end up paying more for this trade credit than for the bank credit that the customer is denied access to. This interpretation goes back at least to Meltzer (1960), and a version of it is built into most of the formal models of trade credit, including Biais and Gollier (1997), Burkart and Ellingsen (2004), and Cuñat (2007). But despite its widespread acceptance, there is hardly any direct empirical evidence supporting this version of the pecking-order hypothesis, as few researchers have had access to transaction data.³

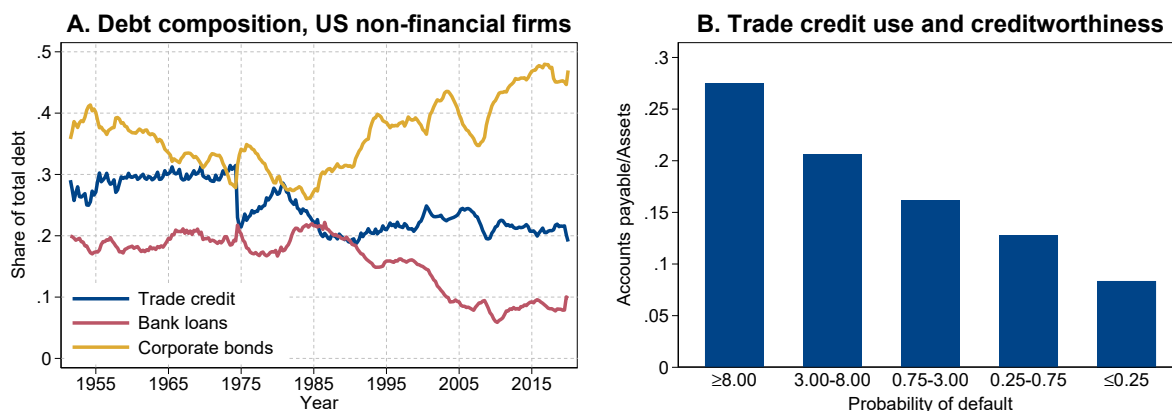
In this paper, we analyze a unique Swedish source of detailed data on trade credit con-

¹The data in Panel A of Figure 1 concern nonfinancial corporate businesses in the U.S., but available evidence suggests that trade credit if anything is an even more important funding source in other developed economies (Rajan and Zingales, 1995; Giannetti, 2003).

²For related observations and discussions see Klapper, Laeven and Rajan (2012), Breza and Liberman (2017), and Giannetti, Serrano-Velarde and Tarantino (2020).

³Meltzer based his conclusions largely on variation in the ratio of receivables to sales during a tight-money episode 1955–57. However, without contract-level data it is difficult to say what actually happened, as he himself acknowledges. For example, it is possible that receivables rose relative to sales because sales to final customers dropped relative to inter-firm sales.

Figure 1: Trade credit in the aggregate and in the cross-section of firms



Panel A shows trade payables, bank loans, and corporate bonds, respectively, as a share of total debt for nonfinancial corporate businesses in the United States, where total debt is defined as the sum of ‘debt securities and loans’ and trade payables (the shares do not sum to 100 percent as some debt classes are omitted from the figure). Panel B shows the average ratio of accounts payable—received trade credit—to total assets (AP_{it}/TA_{it}) across bins of the probability of default distribution for the firms in our sample. The rating variable is described in detail in Section 3.3.

tract terms. The data comprise the whole history of virtually every invoice issued by 46 Swedish suppliers to their 126,000 domestic corporate customers over the period 2005–2008, altogether 21 million invoices. For every customer, we have access to detailed financial accounts data, as well as the credit rating assigned to them by the leading Swedish credit bureau. Thanks to our granular data we are able to examine the pecking-order hypothesis directly. Contrary to conventional wisdom, we find the contracted duration of trade credit to be independent of the customer’s creditworthiness. The actual duration of trade credit is negatively related to creditworthiness, but differences in overdue payments account for less than a sixth of the variation in payables. The remainder is instead due to differences in contract volumes—that is, relative to their assets, less creditworthy firms make larger input purchases.

Does the desire to obtain more trade credit make firms buy more inputs from their suppliers? If so, theories of trade credit need to allow for firms’ choice of input mix. To begin to address the question formally, we generalize the in-kind finance model of Burkart and Ellingsen (2004).

The in-kind finance model centers around the idea that purchase of illiquid inputs mitigates borrower moral hazard by making resource diversion less attractive than when creditors supply liquid loans. Therefore, access to trade credit is particularly valuable to borrowers whose moral hazard problems are large, and who therefore face tighter financial constraints.

To address the input-mix question, we generalize Burkart and Ellingsen (2004) as follows.

Instead of a single input, say a uniform type of labor, we say that the production process takes two steps, and that the firm only needs to hire labor for the last step, say because this step is harder to monitor. For the first step, it can rely on external production; think of this as being conducted by incorporated (i.e., outsourced) labor.⁴ The key assumption is that employed labor cannot be bought on credit to the same extent. The reason is this: When incorporated labor is promised a payment, the corporation can take that promise (to the corporation it is a receivable) and borrow against it. If the corporation subsequently defaults, the bank granting the loan will simply take over the receivable.

By contrast, a worker who gets a job and is offered a payment at the end of the month cannot as easily go to the bank and ask for a loan against the promised paycheck, because the bank cannot merely take over the wage in case the borrower defaults.⁵ Thus, when an employee gives credit, it is making a sacrifice in a way that an incorporated worker is not. As employees are less willing to offer credit, the firm must look for other and potentially more limited sources of funds when using employed labor.

Having designed a theory to fit the observed evidence, the final step of our analysis is to probe the theory's new predictions. The first prediction is that creditworthiness will be positively correlated with the use of employed labor. The correlation is readily available, since firms are required to report both their labor cost and their cost of goods sold. As it turns out, labor's cost share indeed correlates positively with creditworthiness, and the magnitude is sizeable. Compared with firms in the best rating class, the average labor share in the lowest rating class is 17 percent lower.⁶

The second prediction is that financial constraints will lead to greater substitution between employees and external inputs when the external input supplier is in the same industry (and thus offers closer substitutes to what can be produced in-house). Here too, the data offer support. The input distortion is about twenty-seven percent more sensitive to financial conditions when the input seller is in the same industry as the buyer.

⁴Below this is called capital. That will change in the future.

⁵There are virtually always restrictions on wage garnishments, and in many places they are prohibited altogether. In the United States, wage garnishment in connection to private debts are presently prohibited in Pennsylvania, North Carolina, South Carolina, and Texas.

⁶Although we cannot demonstrate conclusively that the correlation is causal, we think that the risk of reverse causality is modest. In particular, we note the following two facts, which contradict the most immediate reverse causality stories: First, our empirical creditworthiness measure takes account of firms' total indebtedness, but does not directly penalize trade debt. Hence, there is no mechanical correlation between creditworthiness and trade credit use. Second, we find that labor adjusts more slowly to negative shocks than input purchases do. Sluggish adjustment to shocks would therefore predict the opposite pattern of what we find.

As far as we know, we are the first to identify a link between financial constraints and a distortion of labor input. In the empirical trade credit literature, Fisman and Love (2003) is the most closely related paper. They find that countries with poorly developed financial markets experience better performance of firms in industries that are more reliant on trade credit. However, their cross-country finding is of a different nature than ours, as it does not require that individual firms choose distorted technologies—it is sufficient that a country’s institutional environment facilitates some industries more than others for their result to arise. By comparison, our within-country study controls for narrowly defined industry categories. Thus, what we document are firm-level distortions. In the financial frictions literature, several papers study the link between frictions and firm-level technology distortion more generally. For example, Gopalan, Mukherjee and Singh (2016) demonstrate that better credit availability due to improved contract enforcement is associated with borrowers holding more long-term assets. There is also a long line of work studying the role of credit market frictions for intangible investment (e.g., Hombert and Matray, 2016, and the references therein). Others have mentioned the related idea that firms might skew investments toward fixed capital in order to attract funding (e.g., Almeida and Campello, 2007).

Beyond the contribution to corporate finance theory, we therefore think that our findings are relevant for the broader literature on financial frictions as a barrier to firm growth. It is widely accepted that much more output could have been produced if it were possible to relax firms’ financial constraints; see, for example, Banerjee and Duflo (2014) and Besley, Roland and Van Reenen (2020) for recent contributions. According to received wisdom, the main problem is either that small firms are unable to fund fixed investment or that many firms are just generally too small. According to our analysis, constrained firms are not only too small in general, but their size deficiency is particularly pronounced in terms of employees.

2 Data and Institutional Setting

2.1 Institutional setting

Accounts payable—received trade credit—is the single largest short-term liability item on Swedish non-financial firms’ balance sheets. In 2007, accounts payable amounted to 11.1 percent of total assets for the average Swedish firm, while short-term bank funding on average amounted to only 2.3 percent of total assets; for the aggregate corporate sector, payables were almost three times as large as short-term bank funding. Virtually all inter-firm trade

is conducted using trade credit: a recent inquiry commissioned by the Swedish government estimates that around 96 percent of the sales of Swedish firms involve trade credit (Pärnhem, 2016). Only exporters and retail firms appear to use cash transactions with any regularity, but trade credit transactions predominate even for these firms. The suppliers appearing in our sample confirm in interviews that close to all sales are made on trade credit; the exceptions being transactions with first-time customers, and with customers that have recently defaulted on trade credit commitments.

The vast majority of trade credit contracts issued by Swedish firms are of the net days variety, which consist of two key contract terms: the amount to be paid and a due date, which defines the maturity of the loan.⁷ The modal maturity for the contracts in our data is 30 days; several firm surveys confirm that this is representative for the Swedish economy more broadly (see, e.g., Pärnhem, 2016, and Intrum Justitia, 2017). Contracts featuring early payments discounts—such as the often discussed “2/10 net 30” contracts, which require that buyers pay within 30 days, while offering a discount of two percent for payments made within ten days—are thus uncommon in Sweden.

These characteristics of trade credit usage in Sweden are similar to those in other developed countries, as can be appreciated by considering the following facts. Firstly, Amberg, Jacobson, von Schedvin and Townsend (2016) show that the ratios of accounts payable and accounts receivable to total assets for Swedish non-financial firms are very close to the corresponding ratios for U.S. Compustat firms. Secondly, Intrum Justitia (2017) presents cross-country survey evidence showing that the average maturity of trade credit contracts in Sweden is very close to the average across all EU/EFTA countries. Moreover, the average number of net days in the contracts in this paper is very close to the average number of net days in the contracts issued by the sample of American firms studied by Giannetti, Burkart and Ellingsen (2011).⁸ Thirdly, Ng, Smith and Smith (1999), Giannetti, Burkart and Ellingsen (2011), and Klapper, Laeven and Rajan (2012), among others, show that early payments discounts are fairly uncommon in trade credit contracts issued by American firms; hence, the dominance of net days contracts over contracts with early payments discounts is also a feature shared

⁷Trade credit contracts may also stipulate a penalty interest rate to be charged should the customer fail to pay on time, but such clauses are not mandatory. If consequences of default have not been explicitly agreed upon, the Interest Rate Act of 1975 stipulates that suppliers have a right to charge a penalty interest rate amounting to a reference rate set by the Swedish central bank plus eight percentage points. If a due date has not been contracted, suppliers can charge the penalty interest rate starting from 30 days after notice of payment has been given.

⁸The contracts in Giannetti, Burkart and Ellingsen (2011), drawn from the National Survey of Small Business Finances (NSSBF), have an average maturity of around 25 days with a standard deviation of 12 days. The corresponding mean and standard deviation in our sample are 30 and 10 days, respectively, when measured at the contract level, and 25 and 8 days when measured at the level of customer-supplier pairs (cf. Table 3).

with other countries.

2.2 Data sources

The empirical analysis in this paper is based on three main data sets, which we merge unambiguously by means of the unique identifier (*organisationsnummer*) attached to each Swedish corporate firm. Firstly, we obtain contract-level data from UC AB (UC), the leading credit bureau in Sweden. The contract-level data contains detailed information on all completed trade credit contracts issued by a sample of Swedish suppliers during the period 2005–2008. For each contract, we observe the identities of the supplier and the customer; the date when the contract was issued; the amount to be paid; the agreed maturity date; and the date of actual payment.

The contract dataset originates from a project launched by the credit bureau in 2003, with the purpose of collecting an entirely new type of input data for their monitoring of trade credit risks in the Swedish economy. The credit bureau recognized the importance of timely input data, and the new project aimed at enabling monitoring of firms' cash flows on a continuous basis—if not in proper real time, at least with a much smaller lag than the six quarters typically associated with financial statements. Representative firms—chosen to reflect a cross-section of suppliers in the economy—were invited to participate in the project by submitting monthly reports on the details of every invoice issued for payment of inputs delivered to customers. In return for this cumbersome undertaking, the credit bureau offered analyses of credit risks in the firms' customer pools using their PD-scoring model. Thus, the project was not run on a strictly commercial basis, but rather as a concern of mutual interest. We interpret the format and the design of the project as attenuating threats of potential selection bias in the set of suppliers, but we nevertheless undertake an evaluation of differences between the suppliers and their industry, age, and size peers, to confirm that view.⁹

Secondly, we obtain firm-level data at annual frequency from the database Serrano, which covers the universe of corporate firms in Sweden. Serrano is constructed based on data from several official sources—most importantly the Swedish Companies Registrations Office, to which all Swedish corporations are required to submit annual financial accounting statements in accordance with EU standards—and comprises detailed accounting data, as well as

⁹The project of systematic collection of invoice data was terminated around 2015, since over time many participating firms chose to discontinue invoice submissions. In a sense the project idea was in 2003 much before its time, amounting to Big and Real time data ideas before the concepts were widely known. With the advancement of IT technology, for efficient data storage and transfer, the likelihood of success has increased and, indeed, a new effort to collect invoice data has recently been launched by the credit bureau.

demographic data, such as a firm's industry, location, and age. Finally, we use an additional data set from the credit bureau UC, which comprises firm-level credit ratings and probabilities of default for the universe of Swedish corporate firms. Taken together, these data sets provide us with rich and detailed information about the trade credit contracts and the characteristics of the contracting parties.

2.3 Sample properties

Our final sample consists of 21.0 million trade credit contracts, issued by 46 suppliers to 126,488 unique customers over the four-year sample period 2005–2008.¹⁰ The customers in the sample are a large and diverse set of firms that jointly make up around half of all non-financial corporations that were active in Sweden during the sample period. The set of suppliers, on the other hand, is rather small and also self-selected, since it consists of firms that actively chose to subscribe to the credit risk monitoring service described in the previous section. In what follows, we describe the characteristics of suppliers and customers in more detail.

We begin with a comparison of the industry, size, and age distributions of sample customers and suppliers, respectively, with the corresponding distributions pertaining to all firms in the Swedish non-financial corporate sector. The results are reported in Table 1. The size and industry distributions of sample customers track the population distributions closely, which is expected given that sample customers constitute roughly half of all firms in the Swedish economy. The set of sample suppliers, on the other hand, is heavily dominated by larger and older firms; for example, firms with more than 1,000 employees make up around 22 percent of the suppliers in our sample, but only 0.1 percent of firms in the population. The industry distribution of sample suppliers tracks the population distribution more closely, although some industries, most notably manufacturing and trade, are over-represented, while other industries, such as real estate and utilities, do not appear at all.

In Table 2, we report descriptive statistics on a broad set of financial and demographic characteristics for four groups of firms: sample suppliers, sample customers, and one comparison group each for suppliers and customers. The comparison groups are constructed by weighting the population of non-financial corporations so that the industry-size-age distribution of the population matches those of sample suppliers and customers, respectively.

¹⁰We describe the sample screens that we use to construct the final sample in Section B1 in Appendix B. Table B1 in the same section details how the sample size and composition changes with the application of each selection screen.

Table 1: Size, age, and industry distribution of customers and suppliers

	Customers	Suppliers	All firms
A. Size distribution			
Micro ($EMPL < 10$)	0.718	0.000	0.823
Small ($10 \leq EMPL < 50$)	0.227	0.119	0.147
Medium ($50 \leq EMPL < 250$)	0.045	0.301	0.025
Large ($250 \leq EMPL < 1000$)	0.008	0.357	0.004
Very large ($EMPL \geq 1000$)	0.002	0.224	0.001
B. Age distribution			
$AGE \leq 2$	0.047	0.000	0.089
$2 < AGE \leq 5$	0.122	0.014	0.149
$5 < AGE \leq 10$	0.176	0.028	0.183
$10 < AGE \leq 15$	0.163	0.028	0.156
$AGE > 15$	0.492	0.930	0.424
C. Industry distribution			
Agriculture and mining (A-B)	0.020	0.000	0.030
Manufacturing (C)	0.162	0.280	0.116
Utilities (D-E)	0.007	0.000	0.005
Construction (F)	0.173	0.021	0.132
Wholesale and retail trade (G)	0.262	0.455	0.242
Transportation and storage (H)	0.055	0.084	0.062
Hotels and restaurants (I)	0.035	0.000	0.042
Information and communication (J)	0.048	0.056	0.056
Real estate (L)	0.035	0.000	0.038
Professional, scientific, and technical activities (M)	0.121	0.042	0.170
Administrative services (N)	0.035	0.063	0.035
Other industries (O-S)	0.047	0.000	0.072
Number of firms	126,488	46	216,423
Number of firm-years	335,757	143	666,541

This table reports the size, age, and industry distributions for sample customers and suppliers, as well as for the Swedish corporate sector as a whole. The letters denoting industries correspond to SNI/NACE sections.

Table 2: Sample representativity

Panel A.	Customers		Population		Normalized difference
	Mean	SD	Mean	SD	
AP_{it}/TA_{it}	0.142	0.137	0.134	0.048	0.079
$AR_{it}/SALES_{it}$	0.107	0.093	0.103	0.031	0.052
TA_{it} (MSEK)	19.187	54.198	17.824	40.911	0.028
$EMPL_{it}$	12.526	23.482	12.046	22.027	0.021
AGE_{it}	17.796	13.663	17.619	10.586	0.014
$RATING_{it}$	3.889	1.075	3.896	0.507	-0.009
DIV_{it}/TA_{it}	0.031	0.061	0.031	0.012	-0.003
$DEBT_{it}/TA_{it}$	0.611	0.265	0.606	0.088	0.026
$CASH_{it}/TA_{it}$	0.220	0.228	0.233	0.079	-0.078
$EBITDA_{it}/TA_{it}$	0.117	0.189	0.115	0.033	0.020
Number of firms	126,488		216,423		
Number of firm-years	335,757		666,541		

Panel B.	Suppliers		Population		Normalized difference
	Mean	SD	Mean	SD	
AP_{jt}/TA_{jt}	0.173	0.118	0.146	0.040	0.312
$AR_{jt}/SALES_{jt}$	0.107	0.052	0.098	0.026	0.215
TA_{jt} (MSEK)	254.733	111.436	226.434	116.713	0.248
$EMPL_{jt}$	116.790	35.810	106.984	37.961	0.266
AGE_{jt}	42.825	19.509	38.461	10.421	0.279
$RATING_{jt}$	4.448	0.766	4.351	0.326	0.164
DIV_{jt}/TA_{jt}	0.029	0.061	0.027	0.011	0.041
$DEBT_{jt}/TA_{jt}$	0.590	0.159	0.623	0.061	-0.270
$CASH_{jt}/TA_{jt}$	0.067	0.094	0.099	0.050	-0.428
$EBITDA_{jt}/TA_{jt}$	0.135	0.115	0.126	0.034	0.108
Number of firms	46		216,423		
Number of firm-years	143		666,541		

This table reports descriptive statistics for four groups of firms: sample suppliers, sample customers, and one comparison group for each. The comparison groups are constructed by weighting the population of Swedish non-financial firms so that the industry-size-age distribution of the population matches those of sample suppliers and customers, respectively. The variables included in the comparison are the following: payables over assets (AP_{it}/TA_{it}), receivables over sales ($AR_{it}/SALES_{it}$), total assets in millions of SEK (TA_{it}), number of employees ($EMPL_{it}$), years since incorporation (AGE_{it}), credit rating ($RATING_{it}$), dividend payments over assets (DIV_{it}/TA_{it}), total debt over assets ($DEBT_{it}/TA_{it}$), cash holdings over assets ($CASH_{it}/TA_{it}$), and operating cash flow over assets ($EBITDA_{it}/TA_{it}$).

The purpose is to assess whether the suppliers and customers are representative of firms of similar size and age operating in the same industry. The key statistic in the comparison is the normalized difference in means, which measures the difference in means between two groups for a given variable, expressed in terms of standard deviations.¹¹

Consider first the comparison of suppliers with their peer firms, reported in Panel A. The normalized differences are overall small—only two out of nine differences substantially exceed 0.3 in absolute value—which suggests that the sample suppliers are reasonably similar to other firms belonging to the same industry-size-age classes.¹² To the extent that the sample suppliers differ from the firms in the comparison group, they appear to be somewhat larger, older, and more creditworthy, but even these differences are rather modest. Importantly, the difference in trade credit issuance between sample suppliers and their peers is small; the average ratio of accounts receivable to sales is 0.107 for sample suppliers and 0.098 for the comparison group. The corresponding comparisons between sample customers and their peer firms, reported in Panel B, show that they are very similar on all characteristics.

In sum, the customers in our sample are representative of the corporate sector across a broad set of demographic and financial characteristics; the suppliers, on the other hand, are substantially larger than the average firm, but reasonably representative of firms belonging to the same industry-size-age group when it comes to financial characteristics and trade credit issuance.

3 Empirical Approach

This section provides the groundwork for the empirical analysis. We begin by demonstrating how accounts payable can be decomposed into its constituent parts in a way that allows us to unveil the underlying drivers of the relationship between financial constraints and accounts payable. We then present the set of dependent variables emanating from the decomposition exercise as well as the independent variable capturing firms' financial constraints. Finally, we discuss the empirical specifications with which we model the variation underlying accounts payable by means of the granular and rich contract data set.

¹¹More specifically, we use the measure of normalized differences proposed by Abadie and Imbens (2011), which is defined as $(\bar{X}_1 - \bar{X}_0) / \sqrt{(S_1^2 + S_0^2)/2}$, where $\bar{X}_i$ and S_i are the means and standard deviations of the comparison variable and i indexes the two groups to be compared. The industry-size-age categories are constructed using the size and age classifications listed in Table 1 combined with two-digit SNI/NACE codes.

¹²We follow Imbens and Rubin (2015) when assessing the size of the normalized differences. More specifically, in an evaluation of the experimental LaLonde (1986) dataset, Imbens and Rubin observe a maximum normalized difference of 0.30, which they judge to be excellent covariate balance.

3.1 Conceptual framework: Decomposing accounts payable

The daily average ratio of accounts payable to total assets on firm i 's balance sheet in year t can be expressed as:

$$\frac{AP_{it}^d}{TA_{it}} = \sum_{c=1}^{N_{it}} \frac{DPAY_{ijct}}{365} \cdot \frac{IPV_{ijct}}{TA_{it}}, \quad (1)$$

where IPV_{ijct} is input purchase value, the value of the inputs purchased by firm i from supplier j in transaction c ; $DPAY_{ijct}$ is days to payment, the number of days between delivery and payment for transaction c , with zero corresponding to a cash transaction; and N_{it} is the number of input purchase transactions undertaken by firm i in year t .¹³ Days to payment and input purchase value can, in turn, be expressed as follows:

$$DPAY_{ijct} = NDAY_{ijct} + DOVER_{ijct} \quad (2)$$

and

$$IPV_{ijct} = P_{ijct} \cdot Q_{ijct}, \quad (3)$$

where $NDAY_{ijct}$ is net days, the contracted duration of the trade credit extended in transaction c ; $DOVER_{ijct}$ is days overdue, the difference between actual and contracted duration; and P_{ijct} and Q_{ijct} are the unit price and the quantity, respectively, of the input purchased by firm i in transaction c .

Equations (1)–(3) make it clear that there are several possible sources of observed variation in the aggregate amount of accounts payable on firms' balance sheets: (i) variation in input purchase value, due to variation in unit prices or quantities of inputs purchased, or both, (ii) variation in contracted duration, and (iii) variation in the deviation from contracted duration due to either early or late payments. A log-additive decomposition of AP_{it}^d/TA_{it} , based on equations (1)–(3), provides a framework for isolating individual components' bearings on the variation in accounts payable. It is easily verified that (1) can be rewritten as

$$\frac{AP_{it}^d}{TA_{it}} = \frac{\overline{DPAY}_{it}}{365} \cdot \frac{\sum_{c=1}^{N_{it}} IPV_{ijct}}{TA_{it}}, \quad (4)$$

where $\overline{DPAY}_{it}$ is the value-weighted average days to payment across all input purchase

¹³Note that accounts payable as defined in (1) may differ from accounts payable as observed on firm i 's balance sheet in year t , since the latter measures the amount of payables outstanding on the last day of the fiscal year. To distinguish between these measures, we use AP_{it}^d/TA_{it} to refer to the daily average of accounts payable in year t , and AP_{it}/TA_{it} to refer to accounts payable as observed on the balance sheet in year t .

transactions c undertaken by firm i in year t , $\overline{DPAY}_{it} = \sum_{c=1}^{N_{it}} DPAY_{ijct} \cdot \omega_{ijct}$, and the weight is defined as $\omega_{ijct} = IPV_{ijct} / \sum_{c=1}^{N_{it}} IPV_{ijct}$. Now, taking the log of (4) yields:

$$\ln \left(\frac{AP_{it}^d}{TA_{it}} \right) = \ln \left(\frac{\overline{DPAY}_{it}}{365} \right) + \ln \left(\frac{\sum_{c=1}^{N_{it}} IPV_{ijct}}{TA_{it}} \right). \quad (5)$$

The log-transformation of AP_{it}^d/TA_{it} thus allows us to express the transformed variable as the sum of its two main components: average days to payment and the total value of input purchases during the year in relation to total assets. It is straightforward to further decompose the latter into the quantity-weighted average unit price and the total quantity of input purchases during the year, respectively, in accordance with (3):

$$\ln \left(\frac{\sum_{c=1}^{N_{it}} IPV_{ijct}}{TA_{it}} \right) = \ln (\overline{P}_{it}) + \ln \left(\frac{\sum_{c=1}^{N_{it}} Q_{ijct}}{TA_{it}} \right) \quad (6)$$

where $\overline{P}_{it} = \sum_{c=1}^{N_{it}} P_{ijct} \cdot \omega_{ijct}^Q$ and $\omega_{ijct}^Q = Q_{ijct} / \sum_{c=1}^{N_{it}} Q_{ijct}$. The term capturing average days to payment, $\ln (\overline{DPAY}_{it}/365)$, cannot readily be decomposed further within (5), however, since $\overline{DPAY}_{it}$ is defined as the sum of its two component parts. Average days to payment is therefore decomposed separately as follows:

$$\overline{DPAY}_{it} = \overline{NDAYS}_{it} + \overline{DOVER}_{it}, \quad (7)$$

where $\overline{NDAYS}_{it} = \sum_{c=1}^{N_{it}} NDAYS_{ijct} \cdot \omega_{ijct}$ and $\overline{DOVER}_{it} = \sum_{c=1}^{N_{it}} DOVER_{ijct} \cdot \omega_{ijct}$.

3.2 Dependent variables

The dependent variables in the empirical analysis are constructed based on the log-additive decomposition of AP_{it}^d/TA_{it} described above. It is important to note, however, that we empirically construct our dependent variables by aggregating the contract-level data up to the match-year level—rather than to the firm level, as in equations (5)-(7) in the previous subsection—since our main empirical models are estimated at the match-year level.

Realized credit.—Our first dependent variable is the log of the ratio of realized credit—the average amount of credit granted from supplier j to customer i on any given day in year t —to

customer i 's total assets:

$$y_{ijt}^1 = \ln \left(\frac{RC_{ijt}}{TA_{it}} \right) = \ln \left(\sum_{c=1}^{N_{ijt}} \frac{DPAY_{ijct}}{365} \cdot \frac{IPV_{ijct}}{TA_{it}} \right), \quad (8)$$

where N_{ijt} is the number of input purchase transactions between customer i and supplier j during year t , and the remaining variables are defined as before. The variable realized credit is thus the match-level correspondent of accounts payable, in the sense that if realized credit is aggregated over all suppliers j of customer i , one obtains the value of customer i 's accounts payable as specified in (1): $\sum_j RC_{ijt} = AP_{it}^d$.

Days to payment.—Our second dependent variable is the log of the weighted average days to payment across all input transactions between customer i and supplier j in year t :

$$y_{ijt}^2 = \ln (\overline{DPAY}_{ijt}) = \ln \left(\sum_{c=1}^{N_{ijt}} DPAY_{ijct} \cdot \omega_{ijct} \right), \quad (9)$$

where $\omega_{ijct} = IPV_{ijct} / \sum_{c=1}^{N_{ijt}} IPV_{ijct}$. Note that we can drop the denominator that appears in the expression in (5), since this is simply a constant that does not affect the estimation results.

Input purchase value.—Our third dependent variable is the log of the total value of the inputs purchased by customer i from supplier j in year t , divided by customer i 's total assets:

$$y_{ijt}^3 = \ln \left(\frac{IPV_{ijt}}{TA_{it}} \right) = \ln \left(\sum_{c=1}^{N_{ijt}} \frac{IPV_{ijct}}{TA_{it}} \right), \quad (10)$$

where $IPV_{ijt} = \sum_{c=1}^{N_{ijt}} IPV_{ijct}$. Note that since we only observe transactions involving trade credit in our data, IPV_{ijt} will understate the true value of input purchases to the extent that cash transactions occur; as discussed in the previous section, however, virtually all inter-firm trade in the Swedish economy involves trade credit, so we deem this a minor concern for the analysis.

Unfortunately, we do not observe unit prices and quantities separately in our data and can therefore in practice not undertake the further decomposition of the value of input purchases outlined in (6).¹⁴ We will nevertheless be able to say something about the extent to which the results regarding input purchases values are accounted for by prices and quanti-

¹⁴Note, however, that in many industries it is in practice often hard to separate the total value of a transaction into a clearly defined unit price and a quantity purchased; this is, for example, likely to be the case in many service industries.

ties, respectively; we will return to this issue when discussing the empirical results in the next section.

Contract maturity.—Our fourth, fifth, and sixth dependent variables are the weighted averages of days to payment, net days, and days overdue, respectively, across all transactions c between customer i and supplier j in year t :

$$y_{ijt}^4 = \overline{DPAY}_{ijt} = \sum_{c=1}^{N_{ijt}} DPAY_{ijct} \cdot \omega_{ijct}, \quad (11)$$

$$y_{ijt}^5 = \overline{NDAYS}_{ijt} = \sum_{c=1}^{N_{ijt}} NDAYS_{ijct} \cdot \omega_{ijct}, \quad (12)$$

$$y_{ijt}^6 = \overline{DOVER}_{ijt} = \sum_{c=1}^{N_{ijt}} DOVER_{ijct} \cdot \omega_{ijct}. \quad (13)$$

Recall that net days is the contracted maturity of the trade credit extended in a given transaction, days to payment is the actual time to payment, and days overdue is the difference between the two. As in the case of IPV_{ijt} , cash transactions would have been problematic for the measurement of $\overline{DPAY}_{ijt}$, $\overline{NDAYS}_{ijt}$, and $\overline{DOVER}_{ijt}$ had they been common—since these variables all take the value zero in cash transactions—but since cash transactions are rare in inter-firm trade, this is not a cause for concern.

We will also consider a version of the days overdue variable that only takes non-negative values:

$$y_{ijt}^7 = \overline{DOVER}^+_{ijt} = \sum_{c=1}^{N_{ijt}} DOVER^+_{ijct} \cdot \omega_{ijct}, \quad (14)$$

where $DOVER^+_{ijct} = \max(DOVER_{ijct}, 0)$.

Table 3 provides descriptive statistics for the contract variables, measured at the level of individual contracts as well as at the level of customer-supplier pairs.

3.3 Independent variable

The independent variable in the empirical analysis is financial constraints, measured by means of the firm-specific credit rating ($RATING_{it}$) assigned to each Swedish corporate firm by the leading Swedish credit bureau, UC AB. UC's rating system comprises five risk classes, 1–5, where higher risk classes are associated with lower credit risk. Firms are assigned to one of the five risk classes based on their firm-specific probabilities of default (PD), estimated by UC

Table 3: Contract characteristics

	Mean	Std. dev.	10th pct.	Median	90th pct.
A. Contract-level characteristics					
IPV_{ijct}	10.007	273.358	0.160	1.427	15.144
$NDAY_{ijct}$	28.842	9.890	14.000	30.000	34.000
$DPAY_{ijct}$	30.409	11.872	15.000	30.000	42.000
$DOVER_{ijct}$	1.568	7.776	-2.000	0.000	6.000
B. Match-level characteristics					
IPV_{ijt}	345.784	6,040.893	2.202	17.344	377.916
IPV_{ijt}/TA_{it} (%)	2.963	9.288	0.015	0.327	5.960
$\ln(IPV_{ijt}/TA_{it})$	-1.192	2.364	-4.188	-1.118	1.785
RC_{ijt}/TA_{it} (%)	0.227	0.785	0.001	0.021	0.420
$\ln(RC_{ijt}/TA_{it})$	-3.925	2.425	-7.024	-3.854	-0.868
$DPAY_{ijt}$	25.927	10.760	12.367	28.667	35.332
$\ln(DPAY_{ijt})$	3.167	0.441	2.515	3.356	3.565
$NDAY_{ijt}$	23.767	8.524	11.335	29.187	31.000
$DOVER_{ijt}$	2.160	7.323	-2.000	0.524	7.876
$DOVER_{ijt}^+$	3.121	6.637	0.000	1.000	8.097
$NCONTRACTS_{ijt}$	34.555	568.209	2.000	10.000	54.000
Number of contracts	20,982,287				
Number of customers	126,488				
Number of suppliers	46				
Number of match-years	607,215				
Number of unique matches	285,631				

This table reports descriptive statistics for the contract variables used in the empirical analysis. Panel A reports statistics at the level of individual contracts, while the statistics in Panel B refer to variables measured at the match-year level, where a match refers to a given customer-supplier pair. Note that the statistics for the ratios IPV_{ijt}/TA_{it} and RC_{ijt}/TA_{it} are expressed in percentage terms, rather than in decimal form. Definitions of all variables are provided in section 3.2 of the text.

by means of a scoring model, where the intervals are as follows: above 8 percent, 3–8 percent, 0.75–3 percent, 0.25–0.75 percent, and below 0.25 percent. Hence, $RATING_{it}$ is a categorical variable constructed through a discretization of the underlying, continuous PD variable. The scoring model generating the PDs is based on very rich input data from four main sources: balance sheet and profit-and-loss data from the firm’s financial accounts; data on injunctions for settlement of payments that the firm has defaulted on, issued by the Swedish Enforcement Agency; information on the private financial status of the firm’s board members, such as injunctions regarding defaulted debt; and demographic information, such as age and industry, as well as the firm’s bank credit history.¹⁵

There are several reasons to consider UC ratings an accurate measure of financial constraints. Firstly, the ratings are external, consistent, and universal appraisals of Swedish firms’ one-year failure risks.¹⁶ Secondly, UC ratings are widely used to evaluate counterparty risks in inter-firm trade, as well as by the Swedish commercial banks when screening prospective borrowers and monitoring granted loans. For the latter purpose, UC ratings (as opposed to ratings from competing credit bureaus) are almost exclusively used, since UC was originally set up in the 1970s as a joint venture by the majority of Swedish banks to provide them with structured data on the credit risks of households and firms.

More generally, Besley, Roland and Van Reenen (2020) show that a firm’s probability of default is a sufficient statistic for the extent to which it is financially constrained in a model of credit contracts with moral hazard. We develop a similar argument based on our theoretical model in Section A2 below. Hence, our empirical measure of financial constraints is well-grounded in theory.

3.4 Empirical specifications

We consider a set of models in which the dependent variables, y_{ijt}^ℓ , correspond to the variables defined in equations (8)-(14). The model specifications take the following form:

$$y_{ijt}^\ell = \Omega_{jt} + \sum_{k=1}^4 \beta_k \cdot \mathbb{1}\{RATING_{it} = k\} + \alpha_i^S + \alpha_i^A + \alpha_i^I + \varepsilon_{it}, \quad \ell = 1, 2, \dots, 7 \quad (15)$$

¹⁵As noted above, accounts payable does not enter the scoring model directly, but only indirectly as a component of total indebtedness, which is included in the model. However, according to the credit bureau, the real-time information on injunctions of payment of defaulted debt—both on part of the firm itself and its board members—is the strongest predictor of future default in the scoring model and thus outweighs the more dated information from financial statements, including indebtedness.

¹⁶Jacobson and Lindé (2000) discuss the accuracy of failure predictions offered by UC ratings, and in particular how they fare over the business cycle.

where subscripts i , j , and t index customers, suppliers, and years, respectively. Ω_{jt} denotes a supplier-year fixed effect; $RATING_{it}$ refers to customer i 's credit rating in year t (the omitted rating class is $RATING_{it} = 5$, which comprises the most creditworthy firms); and α_i^S , α_i^A , and α_i^I are fixed effects capturing customer i 's size, age, and industry, respectively, the former two of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. Standard errors are two-way clustered at the customer and supplier levels, respectively, to account for potential correlation of the errors within supplier and customer clusters.

The design of the models specified in (15) is guided by the following considerations. Firstly, since the analysis deals entirely with the demand side of trade credit, we can include supplier-year fixed effects in the models and thereby absorb all supplier-specific variation in trade credit supply, which alleviates the concern that the results could be driven by some form of endogenous matching between customers and suppliers. Our empirical approach thus resembles Khwaja and Mian's (2008) strategy for isolating bank credit supply shocks—with the difference that whereas Khwaja and Mian use borrower-year fixed effects to isolate variation in supply, we employ supplier-year fixed effects to isolate variation in demand.

Secondly, we do not employ customer or match fixed effects in the models—even though this would be feasible given the structure of the data—since they would absorb a key source of variation in the data, namely, the between-customer variation. The importance of between-customer variation comes from the fact that both the main explanatory variable and several of the dependent variables are quite persistent over time, which implies that there is relatively little within-customer variation in the data to exploit.¹⁷ Hence, a model with customer or match fixed effects would to a large extent be identified by means of variation stemming from small and transitory changes in the underlying PD estimates for customers close to the rating category thresholds, and possibly also by means of measurement error in the data. Instead of customer or match fixed effects, we include customer industry, size, and age fixed effects in the models, which control for several potentially important sources of omitted variable bias, while leaving sufficient variation in the data to properly assess the relationships we are

¹⁷For example, customer-level regressions with $\ln(AP_{it}/TA_{it})$ and $RATING_{it}$ as dependent variables, and a full set of customer dummies as independent variables, yield R^2 s of 0.86 and 0.75, respectively, when estimated using the same set of customers and years as in our baseline specification. With a longer panel, one could obtain slightly more within-customer variation in these and other variables, but the difference would not be that large: when we estimate the same regressions on the period 1998–2015, the longest period available in our accounting and credit rating data, the corresponding R^2 s are 0.72 and 0.60, respectively. Hence, similar considerations would apply even with a longer panel.

interested in.¹⁸

In addition to the main empirical models specified in (15), we consider the following customer-level model:

$$\ln \left(\frac{AP_{it}}{TA_{it}} \right) = \alpha_t + \sum_{k=1}^4 \beta_k \cdot \mathbb{1}\{RATING_{it} = k\} + \alpha_i^S + \alpha_i^A + \alpha_i^I + \varepsilon_{it}, \quad (16)$$

where $\ln(AP_{it}/TA_{it})$ is the log of the ratio of accounts payable to total assets on customer i 's balance sheet in year t ; α_t is a year fixed effect; and the remaining variables are defined as before. Standard errors are clustered at the customer level. As noted above, the models in (15) and (16) differ in that the former are estimated at the match level using contract data, while the latter is estimated at the customer level using accounting data. The purpose of estimating (16) is to assess the generality of the baseline results obtained with the contract-level model in (15); we will return to this issue when presenting the results in the next section.

4 Empirical Results

Our empirical results concern the relationship between trade credit use and financial constraints; in particular, we demonstrate how the constituent parts of accounts payable interact to yield the stylized feature of a negative relationship between trade credit use and creditworthiness. The analyses are conducted for the outcome variables realized credit, input purchase value, days to payment, net days, and days overdue, in accordance with the decomposition described in (1)–(3), and by means of the baseline specification (15) applied to the contract-level data.

4.1 Baseline results

Table 4 reports estimation results for the contract-level model with realized credit, input purchase value, and days to payment, respectively, as outcome variables. Firms in the highest—least risky—rating class ($RATING_{it} = 5$) constitute the reference category; hence, the coefficients capture the estimated difference in the outcome variable for firms in a given rating

¹⁸Including a customer-size fixed effect in the models is not an obvious choice. On the one hand, we want to control for, among other things, size-related technology differences across firms. On the other hand, if firm size and credit rating are jointly determined, then the size fixed effect may distort the estimates. Fortunately, in practice it matters very little for the results whether or not the size fixed effect is included. Results corresponding to those in Tables 4–7 below, but estimated using models without customer-size fixed effects, are available from the authors upon request.

Table 4: Baseline results

	(I)	(II)	(III)
	$\ln\left(\frac{RC_{ijt}}{TA_{it}}\right)$	$\ln\left(\frac{IPV_{ijt}}{TA_{it}}\right)$	$\ln(DPAY_{ijt})$
$RATING_{it} = 4$	0.468 (0.028)	0.427 (0.027)	0.041 (0.002)
$RATING_{it} = 3$	0.569 (0.039)	0.470 (0.037)	0.099 (0.005)
$RATING_{it} = 2$	0.733 (0.073)	0.546 (0.068)	0.187 (0.013)
$RATING_{it} = 1$	0.959 (0.127)	0.617 (0.117)	0.343 (0.026)
Year FE	Yes	Yes	Yes
Customer controls	Yes	Yes	Yes
Supplier-year FE	Yes	Yes	Yes
R^2	0.445	0.440	0.500
Number of customers	126,488	126,488	126,488
Number of suppliers	46	46	46
Number of observations	607,215	607,215	607,215

This table reports the results of estimations of the contract-level model specified in (15) with realized credit, input purchase value, and days to payment as outcome variables. The omitted rating class in all columns is $RATING_{it} = 5$, which comprises the most creditworthy firms. The set of customer controls consists of age, size, and industry fixed effects, the two former of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. The estimation period is 2005–2008 in all columns. Standard errors two-way clustered at the customer and supplier levels, respectively, are reported in parentheses.

class compared with firms in the highest rating class. The results in Column (I) show that realized credit decreases monotonically in credit rating, i.e., firms with worse credit ratings use more trade credit. The magnitude of the relationship is substantial: for example, the average ratio of realized credit to total assets for firms in the lowest rating class is twice as large as for firms in the highest rating class. The estimated negative relationship between creditworthiness and received trade credit is consistent with previous findings in the empirical literature, notably Petersen and Rajan (1997).

Next, we assess to which extent the negative relationship between credit rating and realized credit in the contract-level model is accounted for by input purchase value and days to payment, respectively. Since these two variables emanate from a log-additive decomposition of realized credit—as discussed in Section 3—the coefficients from these separate regressions will, for given rating class, sum to the corresponding coefficient in a regression with realized credit as outcome variable. The exercise thus enables us to directly assess the relative importance of the two components that jointly determine realized credit. The results, reported in Columns (II) and (III), show that both input purchase value and days to payment are monotonically decreasing in rating class, i.e., firms with worse credit ratings buy more inputs on credit and take longer to pay, in comparison with better rated firms. However, the relative importance of the two components differ across rating classes. Input purchase value accounts for most of the relationship between creditworthiness and realized credit in all rating classes, but we find that days to payment is relatively more important for firms in the lower rating classes. The share of the relationship between creditworthiness and realized credit accounted for by days to payment is monotonically decreasing in rating class, falling from 35.8 percent when comparing rating classes 1 and 5, to 8.8 percent when comparing rating classes 4 and 5; the weighted average across all rating classes is 15.6 percent, or slightly less than one sixth.

4.2 Days to payment

The two main components in realized credit can, as established in Section 3, be further decomposed into their respective constituent parts: input purchase value into the unit price and quantity associated with a given contract, and days to payment into the contracted maturity and the deviation of factual maturity from contracted maturity. We will consider these in turn, beginning with maturities. We conduct the decomposition of the relationship between days to payment and credit rating by again estimating the contract-level model, this time with days to payment, net days (contracted maturity), and days overdue (deviation from contracted maturity) as outcome variables. As explained above, we measure these variables in number of days to be able to undertake an additive decomposition of days to payment. Hence, we will begin by re-estimating the contract-level model with days to payment as outcome variable, but now measured in levels instead of logs. The results, reported in Column (I) of Table 5, confirm that days to payment measured in levels is monotonically decreasing in credit rating: for example, the estimated difference in days to payment between firms in rating classes 1 and 5 is over eleven days, but only one day when comparing firms in rating

Table 5: Decomposing days to payment

	(I)	(II)	(III)	(IV)
	$DPAY_{ijt}$	$NDAYS_{ijt}$	$DOVER_{ijt}$	$DOVER_{ijt}^+$
$RATING_{it} = 4$	1.013 (0.098)	-0.041 (0.033)	1.054 (0.074)	0.788 (0.060)
$RATING_{it} = 3$	2.610 (0.193)	-0.014 (0.038)	2.624 (0.172)	2.213 (0.165)
$RATING_{it} = 2$	5.371 (0.408)	-0.066 (0.042)	5.436 (0.400)	4.981 (0.404)
$RATING_{it} = 1$	11.180 (0.995)	-0.067 (0.072)	11.247 (0.977)	10.871 (0.970)
Year FE	Yes	Yes	Yes	Yes
Customer controls	Yes	Yes	Yes	Yes
Supplier-year FE	Yes	Yes	Yes	Yes
R^2	0.435	0.602	0.189	0.208
Number of customers	126,488	126,488	126,488	126,488
Number of suppliers	46	46	46	46
Number of observations	607,215	607,215	607,215	607,215

This table reports the results of estimations of the contract-level model specified in (15) with days to payment, net days, days overdue, and non-negative days overdue as outcome variables. The omitted rating class in all columns is $RATING_{it} = 5$, which comprises the most creditworthy firms. The set of customer controls consists of age, size, and industry fixed effects, the two former of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. The estimation period is 2005–2008 in all columns. Standard errors two-way clustered at the customer and supplier levels, respectively, are reported in parentheses.

classes 4 and 5. The difference in days to payment between high-rated and low-rated firms is thus substantial, given that the mode maturity in our contract data is 30 days.

The results for the estimations with net days and days overdue as outcome variables are reported in Columns (II) and (III), respectively. A clear pattern emerges: for net days, the coefficients are close to zero and statistically insignificant across all rating classes, whereas the coefficients in the days overdue regression are statistically significant and essentially equal in magnitude to the corresponding coefficients in the estimations with days to payment. Hence, the negative relationship between creditworthiness and days to payment across rating classes

is entirely accounted for by differences in days overdue. Note, however, that since the variable $DOVER_{ijt}$ takes both negative and positive values—i.e., it captures both premature and late payments—we have not yet demonstrated that the findings just reported are driven by differences in late payments across rating classes. To do so, we estimate the contract-level model with $DOVER_{ijt}^+$, which only records late payments, as outcome variable. The coefficients, reported in Column (IV), are very close to those in the estimation with $DOVER_{ijt}$, which shows that the negative relationship between rating class and days to payment is due to differences in late payments. We conclude that financially weak firms exercise a non-negligible amount of overdrafting, or temporary defaulting, on trade credit debt. This finding highlights the insurance aspect of trade credit, as discussed by Cuñat (2007), and more recently by Amberg, Jacobson, von Schedvin and Townsend (2021).

4.3 Input purchase values

Consider next the question of the extent to which the negative relationship between input purchase value and rating class is accounted for by variation in prices and quantities, respectively. As noted, our contract data do not comprise prices and quantities and we are therefore unable to provide direct evidence on this issue. Nonetheless, we can cast some light on the roles played by prices and quantities in accounting for the negative relationship. In brief, we argue that price differences can explain only a smaller fraction of this relationship, and consequently that the negative relationship between creditworthiness and input purchase value is primarily due to firms with worse credit ratings buying larger quantities of intermediate inputs. Our argument considers two likely reasons for why the unit price of a given input may vary between firms in different rating classes. The first is volume discounts; if suppliers offer lower unit prices when customers buy larger quantities, and creditworthiness is positively correlated with firm size, then prices could be decreasing with the credit rating of the customer because of volume discounts. However, the set of firm-level covariates in our regressions includes firm size, which controls for the possibility that more highly rated firms are more often offered volume discounts.

A second reason for unit prices to decrease in creditworthiness is that suppliers may incorporate the default risk of the customer into the price when selling inputs on credit.¹⁹ While we believe that price effects may be present in our results, we find it unlikely that they ac-

¹⁹Amberg, Jacobson and von Schedvin (2020) provide empirical evidence showing that product prices in transactions involving trade credit include a credit risk component; Jacobson and von Schedvin (2015) examine the propagation of failure risk in trade credit chains.

count for more than a fraction of the negative relationship between input purchase value and rating class. The following example spells out the argument: what would be the difference in the prices charged by a risk-neutral supplier when selling identical goods on 30-day credit periods to customers with annual default probabilities of 20 and 0.1 percent?²⁰ The answer is around 1.8 percent, which is not nearly large enough to explain the magnitude of the relationship between rating class and input purchase value; recall that the estimated difference in input purchase value between firms in the highest and lowest rating classes is over 60 percent (Table 4, Column II).^{21,22} While this example is deliberately simplistic—many real life suppliers are no doubt risk averse, which could motivate higher price differentials—it suggests that even when allowing for the largest plausible differences in prices facing firms in different rating classes, they still fall short of explaining more than a fraction of the differences in input purchase value implied by our analysis. Hence, the negative relationship between input purchase value and rating class is predominantly accounted for by variation in quantities.

4.4 Generality of findings

We turn next to an assessment of the generality—or external validity—of the baseline results. Firstly, recall that we only observe a subset of the suppliers of each customer in the contract data, which raises the question of whether these suppliers are representative of the rest of the sample customers’ suppliers in terms of extending trade credit. We address this question by estimating the firm-level model specified in (16) for the outcome variable accounts payable, which comprises trade credit received from all of a customer’s suppliers, and comparing the resulting coefficients with the corresponding coefficients from the estimation of the contract-level model with realized credit as outcome variable. Since realized credit is the contract-level correspondent of accounts payable, the results from these estimations should be similar if the suppliers in the contract data are representative of the rest of the sample customers’ suppliers.

The estimations of the contract-level and firm-level models are reported in Columns (I)

²⁰These annual default probabilities approximately correspond to the average values in rating classes 1 and 5, respectively.

²¹To obtain the price difference, simply compute the monthly default probabilities implied by the annual default probabilities using the following formula: $PD_M = 1 - (1 - PD_Y)^{1/12}$; the difference between the two monthly default probabilities is then equal to the price difference that the risk-neutral supplier would charge. In this case, the 20 and 0.1 percent annual default probabilities correspond to monthly default probabilities of 1.84 and 0.01 percent, respectively, which yields a difference of 1.83 percent.

²²We do not mean to imply that firm-level price differences driven by variation in default risks are therefore economically insignificant in general; for example, a price difference of 1.8 percent between high- and low-rated firms is substantial in the context of macro-level inflation dynamics.

Table 6: Assessing the generality of the baseline results

	(I)	(II)	(III)
	$\ln\left(\frac{RC_{ijt}}{TA_{it}}\right)$	$\ln\left(\frac{AP_{it}}{TA_{it}}\right)$	$\ln\left(\frac{AP_{it}}{TA_{it}}\right)$
$RATING_{it} = 4$	0.468 (0.028)	0.527 (0.006)	0.604 (0.005)
$RATING_{it} = 3$	0.569 (0.039)	0.802 (0.007)	0.930 (0.006)
$RATING_{it} = 2$	0.733 (0.073)	1.041 (0.010)	1.227 (0.008)
$RATING_{it} = 1$	0.959 (0.127)	1.328 (0.013)	1.583 (0.010)
Year FE	Yes	Yes	Yes
Customer controls	Yes	Yes	Yes
Supplier-year FE	Yes	—	—
Estimation sample	Contract data	Contract data	All firms
R^2	0.445	0.297	0.308
Number of customers	126,488	126,488	216,423
Number of suppliers	46		
Number of observations	607,215	335,757	666,541

Column (I) reports the results of estimations of the contract-level model specified in (15) with realized credit as outcome variable, whereas Columns (II) and (III) report estimation results for the customer-level model in (16) with accounts payable as outcome variable. The estimation sample comprises the customers in the contract dataset in Columns (I)-(II) and all firms in the Swedish corporate sector in Column (III). The omitted rating class in all columns is $RATING_{it} = 5$, which comprises the most creditworthy firms. The set of customer controls consists of age, size, and industry fixed effects, the two former of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. The estimation period is 2005–2008 in all columns. Standard errors two-way clustered at the customer and supplier levels, respectively, are reported in parentheses.

and (II), respectively, of Table 6.²³ The results show that received trade credit decreases monotonically with rating class in both models, and while the relationship is more pronounced in the customer-level model—for example, the difference between the coefficients for the lowest rating class is almost 40 percent—the coefficients are largely comparable across the two

²³Note that the estimation results reported in Column (I) of Table 6 refer to precisely the same estimation as in Column (I) of Table 4—we simply reprint the results to facilitate the comparison of the two models.

models. Hence, the contract-level model appears to generate findings of general applicability for the sample customers, despite the fact that we only observe a subset of their suppliers.

A second question regarding the generality of the baseline results is whether the sample customers themselves are representative of firms in the Swedish corporate sector when it comes to the relationship between received trade credit and creditworthiness. We address this question by estimating the firm-level model in (16) for the universe of corporate firms in Sweden. The resulting coefficients, reported in Column (III), are comparable to the corresponding coefficients from the estimation based on the sample customers reported in Column (II), although the former are of slightly larger magnitudes. This suggests that the baseline results apply more broadly, which is not surprising given that the sample customers constitute a very large share of the population of Swedish corporate firms.

4.5 Summary of findings

The findings reported in this section can be summarized as follows. Firstly, we find a strong negative relationship between creditworthiness and trade credit use, a relationship that holds in estimations using contract-level data, as well as in more conventional firm-level estimations based on accounts payable. Secondly, we use our contract-level data to document that this relationship is primarily accounted for by lower input purchase values for financially stronger firms, but that a non-trivial share is due to differences in the actual duration of received trade credit. Thirdly, we argue that the likely explanation for the negative relationship between creditworthiness and input purchase value is that firms with worse credit ratings buy larger quantities of intermediate inputs, rather than paying higher unit prices. Finally, we document that the negative relationship between creditworthiness and days to payment is accounted for entirely by differences in late payments across rating classes, and not at all by differences in contracted maturities.

The findings are hard to reconcile with prominent theories of trade credit (e.g. Biais and Gollier, 1997; Burkart and Ellingsen, 2004; and Cuñat, 2007). These theories portray trade credit as a costly and inferior alternative to bank credit, and thus predict that bank credit should substitute for trade credit as firms' financial constraints are relaxed. That is, average contract duration should fall. The lack of an economically meaningful impact of creditworthiness on contracted duration reject that prediction. While we do find a reduction in overdue payments, most of the reduction in payables is instead driven by reduced input purchases. In the next section, we develop the idea that trade credit is being used to expand overall borrow-

ing, possibly at no additional funding cost, rather than to substitute for cheaper bank credit.

5 Theory

We initially generalize the model of Burkart and Ellingsen (2004) merely by letting the firm use employed labor in addition to purchased inputs.

A firm's output is given by the Cobb–Douglas technology

$$Y = K^\alpha L^\beta,$$

where $\alpha + \beta = \gamma < 1$. We think of K , the (working) capital, as comprising the non-labor inputs that are bought on a regular basis. Other long-term investments are sunk. Like the entrepreneurial input they are compensated by the profit.

It takes one month to produce the output. Both the capital input market and the labor market are perfectly competitive. Normalize the price of output and the price of L to 1, and let p denote the price of K .

Let the firm be run by a penniless entrepreneur.²⁴ Let workers be unable or unwilling to lend to the employer. The entrepreneur is assumed to be perfectly patient, so we can neglect discounting.

5.1 Unconstrained problem

Suppose first that contracting is frictionless and that funding is freely available from a competitive credit market. Normalizing this interest rate to 0, the firm's profits are

$$\pi = Y - pK - L.$$

As a benchmark, consider the familiar unconstrained problem:

$$\max_{K,L} \pi(K, L)$$

and its solution

²⁴Introducing positive wealth does not change the qualitative conclusions, but makes it considerably harder to express the conditions under which the firm is financially constrained. We postpone the introduction of receivables.

$$L^* = \alpha^{\frac{\alpha}{1-\alpha-\beta}} \beta^{\frac{1-\alpha}{1-\alpha-\beta}} p^{\frac{-\alpha}{1-\alpha-\beta}}, \quad K^* = \alpha^{\frac{1-\beta}{1-\alpha-\beta}} \beta^{\frac{\beta}{1-\alpha-\beta}} p^{\frac{\beta-1}{1-\alpha-\beta}}.$$

Note that

$$\frac{pK^*}{Y(K^*, L^*)} = \alpha \quad (17)$$

and

$$\frac{L^*}{Y(K^*, L^*)} = \beta. \quad (18)$$

In the unconstrained solution, capital input costs as a fraction of total input costs is

$$\frac{pK^*}{pK^* + L^*} = \frac{\alpha}{\alpha + \beta}. \quad (19)$$

5.2 Constrained problem with bank credit only

Suppose now that borrowing is constrained by the prospect of strategic default. That is, rather than investing borrowed funds and inputs, the entrepreneur may divert them.

Consider first the case in which banks do all the lending. Denote the borrowed amount by B . Diversion would allow the borrower to keep a fraction ϕ of the diverted amount. This *creditor vulnerability* parameter drives credit rationing in the model. When comparing across jurisdictions, we think of variation in ϕ as reflecting differences in the strength of legal enforcement. Within a jurisdiction, we think of variation in ϕ as reflecting differences in relationship-strength. The constrained problem can be written:

$$\max_{B, K, L} Y(K, L) - B$$

s.t.

$$L + pK \leq B, \quad (20)$$

$$Y(K, L) - B \geq \phi B. \quad (21)$$

Call this Program BC (for bank credit). The first constraint says that the firm cannot acquire more labor and capital than it can fund. The second constraint says that borrowing is potentially limited by the moral hazard of diversion.

In order for the borrowing constraint to be binding, we must have

$$Y(K^*, L^*) - pK^* - L^* < \phi(pK^* + L^*).$$

Inserting the unconstrained solution and simplifying—or simpler, dividing through by $Y(K^*, L^*)$ and then using (17) and (18)—we see that the borrowing constraint binds if and only if

$$\phi > \frac{1 - \alpha - \beta}{\alpha + \beta}. \quad (22)$$

That is, the firm is financially constrained if it is relatively easy to divert and if returns to scale decrease slowly. If it is sufficiently easy to scale up the activity, the firm is always constrained as long as $\phi > 0$. According to the model, then, the deep determinant of financial constraints is ϕ .

A remark is in order: In the model, ϕ is our measure of (the inverse of) creditworthiness. Yet, there is no actual default in equilibrium. In Appendix A we introduce uncertainty about the ex post value of ϕ in order to connect the parameter to a positive equilibrium default risk.

Program BC has an analytical solution, which can be found straightforwardly using Lagrange's method. When the constraint binds, the firm scales back both inputs proportionally,

$$(K, L) = [(1 + \phi)(\alpha + \beta)]^{\frac{1}{\alpha + \beta - 1}} (K^*, L^*).$$

Note that the coefficient $(1 + \phi)(\alpha + \beta)$ is larger than 1 when (22) holds, so due to the negative exponent, $(K, L) < (K^*, L^*)$.

5.3 Input illiquidity and trade credit

Suppose finally that suppliers can also lend. If their cost of funds is larger than that of banks, they need to charge (explicit or implicit) interest on their loans. The price of inputs sold on credit is thus denoted $\hat{p}$, with $\hat{p} \geq p$. (We partially endogenize $\hat{p}$ in Section 5.7.)

Like Burkart and Ellingsen (2004) we make three additional assumptions. First, it is more difficult to divert capital than to divert cash; it costs an additional fraction $1 - \delta$ of the value of the capital. We refer to δ as the *input liquidity*. When the input is a service or a tailor-made product with little second-hand value, the liquidity δ is close to 0; if the input is gold or diamonds, the liquidity is close to 1. Second, unlike suppliers who automatically observe customers' input purchases, banks observe neither the input purchase nor the amount of trade credit obtained. Thus, bank credit cannot be explicitly conditioned on either of these two variables.²⁵

²⁵In reality, banks sometimes organize schemes that are based on close monitoring of input transactions, but for brevity we leave the analysis of such supply-chain finance schemes aside here.

Let K^{BC} and K^{TC} denote the capital that is paid with bank credit and trade credit respectively. Then, the general problem takes the form

$$\max_{K^{BC}, K^{TC}, L, B} Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B$$

s.t.

$$pK^{BC} + L \leq B, \quad (23)$$

$$Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B \geq \phi(B + \delta pK^{TC}) \quad (24)$$

(together with non-negativity constraints). Call this Program TC (for trade credit). The first constraint is familiar from Program BC; concerning inputs not bought on trade credit, the firm cannot acquire any more of them than it can raise money in the bank. The second constraint is the central condition of the in-kind finance model, namely that the firm should not buy from the input supplier and then divert both the inputs and the bank loan. Note that in the case of diversion, the borrower purchases neither labor nor capital for the bank loan.²⁶ Whenever $\delta < 1$, the second condition implies that purchases paid with trade credit, K^{TC} , represent a smaller moral hazard than (the merely promised) purchases of L and K^{BC} .

Due to the asymmetry between L and K^{BC} on the one hand and K^{TC} on the other, Program TC is much more mathematically challenging than Program BC. It does not generally possess an analytical solution, and so must be solved numerically. Since the solution depends on the technology coefficients α and β , we estimate them before presenting the numerical analysis. Specifically, we rely on the data to tell us the fractions $pK/(pK + L)$ and $L/(pK + L)$, which we know correspond to $\alpha/(\alpha + \beta)$ and $\beta/(\alpha + \beta)$ for an unconstrained firm. The data will also tell us the magnitude of heterogeneity in the factor proportions that the theory is challenged to explain.

5.4 Empirical input distortion

We estimate a version of the model specified in (16) in which the outcome variable is the share of labor costs in total input costs:

$$\frac{L_{it}}{L_{it} + K_{it}} = \alpha_t + \sum_{k=1}^4 \beta_k \cdot \mathbb{1}\{RATING_{it} = k\} + \alpha_i^S + \alpha_i^A + \alpha_i^I + \varepsilon_{it}. \quad (25)$$

²⁶The formulation presupposes that the firm either produces or diverts. As demonstrated by Burkart and Ellingsen (2004) this assumption is without loss of generality: Diversion is never part of an optimal solution, and any contract that deters the firm from diverting all resources also deters partial diversion.

Table 7: Financial constraints and the labor share

	(I)	(II)
$RATING_{it} = 4$	−0.014 (0.001)	−0.020 (0.001)
$RATING_{it} = 3$	−0.037 (0.001)	−0.050 (0.001)
$RATING_{it} = 2$	−0.058 (0.002)	−0.080 (0.001)
$RATING_{it} = 1$	−0.060 (0.002)	−0.084 (0.002)
Year FE	Yes	Yes
Customer controls	Yes	Yes
Estimation sample	Contract data	All firms
R^2	0.356	0.330
Number of customers	121,000	209,330
Number of observations	318,074	641,596

This table reports estimation results for the customer-level model specified in (25) with the share of labor costs in total input costs as outcome variable. The estimation sample comprises the customers in the contract data set in Column (I) and all firms in the Swedish corporate sector in Column (II). The omitted rating class in all columns is $RATING_{it} = 5$, which comprises the most creditworthy firms. The set of customer controls consists of age, size, and industry fixed effects, the two former of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. The estimation period is 2005–2008 in all columns. Standard errors two-way clustered at the customer and supplier levels, respectively, are reported in parentheses.

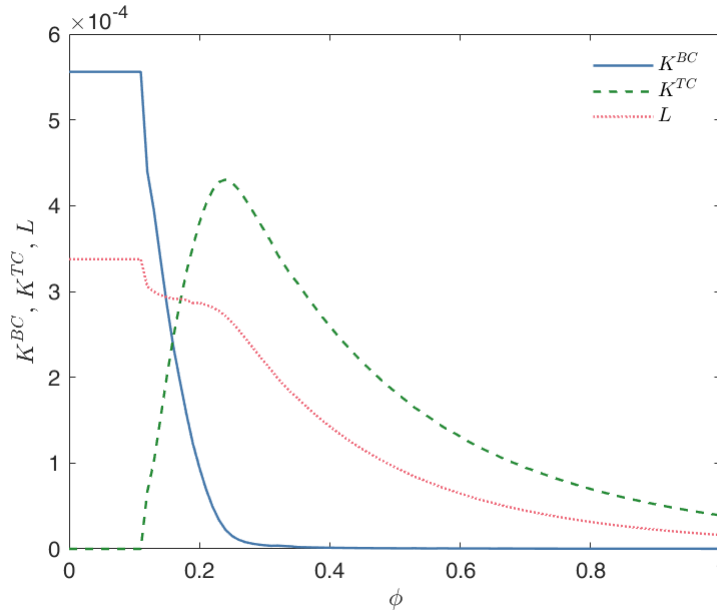
We first estimate (25) on a sample comprising the customers in the contract data. The results, reported in Column (I) of Table 7, show that labor costs increase monotonically as a share of total input costs when firms' creditworthiness improves.²⁷ For example, the labor share is 6.0 percentage points higher among firms in the highest rating class than among firms in the lowest rating class; with an average labor share around 36 percent for sample firms in

²⁷Note that the number of firms is somewhat lower in the estimations reported in Table 7 than in the previous estimations. This is because some firms use the cost of sales method, an accounting standard in which the cost of intermediate inputs is not reported separately. These firms thus lack data for the outcome variable $L_{it} / (L_{it} + K_{it})$ and therefore cannot be included in the estimation.

the highest rating class, this corresponds to a difference of almost 17 percent.²⁸ In Column (II), we report the results when estimating (25) on a sample comprising all corporate firms in Sweden. The resulting coefficients, reported in Column (II) of Table 7, are comparable to the corresponding coefficients in Column (I), which shows that the positive relationship between creditworthiness and the labor share is not particular to the customers in the contract data.

Can the model match this magnitude of variation in the labor share? If so, can it still justify that even the firms that have the highest labor shares prefer to pay high implicit interest rates on trade credit rather than funding all input purchases through bank credit?

Figure 2: Funding as a function of creditor vulnerability

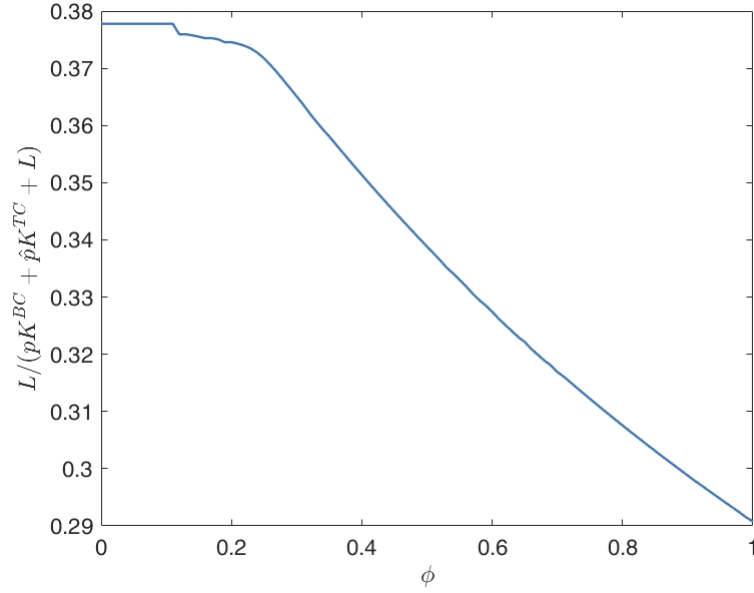


The figure shows how the firm funds input purchases with trade credit and bank credit respectively for different values of creditor vulnerability. It also depicts the amount of labor that the firm employs. The figure is drawn under the assumption that the monthly interest rate on trade credit is one percent ($\hat{p} = 1.01$) and that input liquidity is $\delta = 1/5$.

To answer these questions, let us initially assume that firms differ only in their creditworthiness, as measured by the creditor vulnerability parameter ϕ . Let $\alpha = 1/2$ and $\beta = 3/10$, so that the optimal labor share is $17/45 \approx 0.378$. This justifies the observed labor share of about 0.36 for the highest rating category in our data set (we consider it unlikely that about half of all firms are entirely unconstrained). Furthermore, set input liquidity $\delta = 1/5$, to reflect that

²⁸In aggregate statistics, which measure the value added shares, the labor share is close to $2/3$. The difference reflects the number of processing stages, with the last firm in a production chain typically having a relatively low labor cost, since it uses highly refined other input.

Figure 3: Labor share and creditworthiness



The figure shows how the firm's labor share depends on creditor vulnerability. Parameters are the same as in Figure 2

the capital input is difficult to divert, but not impossible. Suppose the supplier is somewhat financially constrained, with an opportunity cost of funds of 1 percent per month above the bank rate, i.e., $\hat{p} = 1.01$. How large must the customer's creditor vulnerability ϕ be in order for there to be any trade credit? How large must it be for *all* supplies to be funded with trade credit? Figure 3 depicts the answer.

Recall that the first-best outcome requires $\phi \leq (1 - \alpha - \beta)/(\alpha + \beta)$, which here corresponds to $\phi \leq 1/9$ (see (22)). For lower values of ϕ , the customer takes no trade credit, because of the extra cost that it entails. Once creditworthiness deteriorates beyond this point, i.e., $\phi > 1/9$, demand for trade credit increases rapidly, as the drop in bank credit supply forces the firm to prioritize the purchase of labor input, which cannot be funded from other sources. Initially, overall investment falls because of the higher marginal cost of funds, but the firm is still not quantity constrained.

However, as bank funds become ever more scarce, the firm is forced to cut labor purchases below the level that would be justified by marginal cost alone. Thus, the marginal return to investment at the existing input mix rises above the marginal cost. Since capital suppliers are still willing to lend, the firm accepts a less favorable input mix in order to prevent overall

investment from falling too much. Figure 4 illustrates how the labor share drops as creditworthiness falls (i.e., ϕ increases). Under our choice of parameters, the drop in the example matches well the six percentage point drop in the data.

5.5 Heterogeneity in the elasticity of substitution

Our theory predicts that the effect of changes in creditworthiness on the input mix—and therefore also on the ratio of accounts payable to assets—should be stronger for firms with a higher elasticity of substitution between labor and intermediate inputs. To test this, we estimate the following variation on the baseline specification:

$$y_{ijt}^{\ell} = \Omega_{jt} + \sum_{k=1}^4 \beta_k \cdot \mathbb{1}\{RATING_{it} = k\} + \sum_{k=1}^4 \gamma_k \cdot \mathbb{1}\{RATING_{it} = k\} \cdot SI_{ijt} + \phi \cdot SI_{ijt} + \alpha_i^S + \alpha_i^A + \alpha_i^I + \varepsilon_{it}, \quad (26)$$

where SI_{ijt} is an indicator variable equal to one if buyer i and supplier j operates in the same two-digit industry in year t , and all other variables are defined as before. The idea is that the substitution elasticity on average is higher when the buyer and the supplier operate in the same industry and that the baseline result therefore should be stronger in these cases.

The estimation results are reported in Table 8. The results in columns (1) and (2) show that the relationship between creditworthiness and trade credit use indeed is stronger when the supplier and the buyer operate in the same industry. More specifically, the estimated effect is between one-fifth and one-third larger for same-industry pairs. Columns (3) and (4) demonstrate that this effect is entirely driven by the size of input purchases, in line with the theory; the relationship between creditworthiness and days to payment, on the other hand, is not at all affected by the supplier and the buyer operating in the same industry, as shown in columns (5) and (6).

5.6 Competing explanations?

Let us finally consider two alternative explanations for why tighter financial constraints are associated with a lower labor share.

First, adjustment costs might be higher for intermediate goods and services than for labor. As firms are subject to negative shocks, they would then cut back on labor first. To assess the relative adjustment costs for labor and intermediate inputs, we estimate the following

Table 8: Heterogeneity in the elasticity of substitution

	$\ln \left(\frac{RC_{ijt}}{TA_{it}} \right)$		$\ln \left(\frac{IPV_{ijt}}{TA_{it}} \right)$		$\ln (DPAY_{ijt})$	
	(1)	(2)	(3)	(4)	(5)	(6)
	β^k	γ^k	β^k	γ^k	β^k	γ^k
$RATING_{it} = 4$	0.681*** [0.026]	0.117*** [0.043]	0.659*** [0.023]	0.114*** [0.042]	0.021*** [0.006]	0.002 [0.005]
$RATING_{it} = 3$	0.816*** [0.032]	0.172*** [0.045]	0.748*** [0.027]	0.171*** [0.041]	0.068*** [0.008]	0.001 [0.009]
$RATING_{it} = 2$	1.015*** [0.065]	0.285*** [0.067]	0.864*** [0.057]	0.302*** [0.065]	0.150*** [0.012]	0.018 [0.016]
$RATING_{it} = 1$	1.273*** [0.120]	0.422*** [0.145]	0.967*** [0.105]	0.463*** [0.135]	0.306*** [0.021]	0.042 [0.030]
Number of buyers	126,490		126,490		126,490	
Number of suppliers	46		46		46	
Number of observations	607,230		607,230		607,230	
R^2	0.364		0.339		0.482	

This table reports the results of estimations of the contract-level model specified in (15) with days to payment, net days, days overdue, and non-negative days overdue as outcome variables. The omitted rating class in all columns is $RATING_{it} = 5$, which comprises the most creditworthy firms. The set of customer controls consists of age, size, and industry fixed effects, the two former of which are based on the size and age categories listed in Table 1, and the latter on five-digit SNI/NACE codes. The estimation period is 2005–2008 in all columns. Standard errors two-way clustered at the customer and supplier levels, respectively, are reported in parentheses.

customer-level regression:

$$\Delta [L_{it} / (L_{it} + K_{it})] = \alpha_t + \beta \cdot \Delta Sales_{it} + \alpha_i^S + \alpha_i^A + \alpha_i^I + \varepsilon_{it}. \quad (27)$$

where $\Delta [L_{it} / (L_{it} + K_{it})]$ is the change in the labor share of input costs between years $t - 1$ and t , and $\Delta Sales_{it}$ is firm i 's sales growth in year t , measured using the symmetric growth rate formula and with the sales figures adjusted for changes in inventories. The fixed effects are as before. We only include firms in the highest rating class in the estimation. The estimate (t -statistic) of β is -0.017 (-7.7), which implies that adjustment costs are higher for labor inputs than for intermediate goods and services. Hence, asymmetric adjustment costs cannot account for the findings in Table 7.

Second, our analysis has focused on credit rationing due to problems of strategic default. But could not similar input distortions arise for reasons of imperfect competition and non-strategic default alone? The argument is that suppliers of capital inputs have more market

power than workers and banks have. Therefore, they might potentially be willing to take on more credit risk, as suggested by Wilner (2000). As it turns out, this argument is not as clear-cut as it may seem. In Appendix A, we consider the case in which banks (and the labor market) are perfectly competitive, the capital input supplier is a monopolist, and the default probability is independent of the scale of the firm. In this case, the default probability has a symmetric effect on the interest charged by the bank and the price charged by the input supplier. Therefore, there is no impact of the default probability on the input mix. In other words, adding imperfect competition and non-strategic default will help to explain input price differences, but does not immediately contribute to explaining technology differences.

5.7 The trade credit interest rate

Our analysis establishes that all firms like to receive trade credit if they can obtain it without paying a penalty interest rate, and that many firms are even willing to take trade credit at a considerably higher rate. But at what interest rate are sellers willing to supply credit? Will a seller that is credit constrained ever be willing to offer trade credit at the bank rate?

Suppose the period starts with the firm making a sale of the previous period's output. Let the value of these sales be denoted ω . Suppose the firm considers two options. Either it sells the input at cash terms or it provides trade credit at zero interest rate.

If the firm sells for cash, the full problem becomes:

$$\max_{K^{BC}, K^{TC}, L, B} Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B$$

s.t.

$$pK^{BC} + L \leq B + \omega, \quad (28)$$

$$Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B \geq \phi(B + \omega + \delta pK^{TC}) \quad (29)$$

(together with non-negativity constraints). Call this Program F1 (F denotes full). The firm treats the own cash exactly as it treats the bank loan. It either uses all the cash to buy inputs or it diverts it. (Again, intermediate outcomes can be neglected.)

If instead the firm provides credit, without charging any interest, the full problem becomes:

$$\max_{K^{BC}, K^{TC}, L, B} Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B$$

s.t.

$$pK^{BC} + L \leq B, \quad (30)$$

$$Y(K^{BC} + K^{TC}, L) - \hat{p}K^{TC} - B + \omega \geq \phi(B + \delta pK^{TC}) \quad (31)$$

(together with non-negativity constraints). Call this Program F2. Note how the previous period's sales revenues move from the right hand side of the constraints to the left hand side, because the revenues are now tied up in receivables rather than being available as cash. Thus, the firm cannot use its revenue to fund input purchases directly. It also cannot divert these revenues, because receivables are collateralized. The firm only gets access to (what remains of) last period's revenues after it has repaid the bank loan B .

Proposition 1 *The maximum profit associated with Program F2 is identical to the maximum profit associated with Program F1. Thus, regardless of ϕ and δ , the firm is willing to offer trade credit without charging interest.*

The proof follows immediately from the observation that the two problems are isomorphic, except B in F1 corresponds to $B - \omega$ in F2. Thus, whatever the firm is able to borrow in Program F1, it will be able to borrow ω more in F2. That is, by refraining from cashing in the receivables at the beginning of the period, the entrepreneur can raise exactly the same amount in the form of an additional loan. Even if the firm charges no extra interest for its trade credit, it has nothing to lose by offering it.

With hindsight, the result is as obvious: Since receivables cannot be diverted, and are as valuable to creditors as to the firm, they constitute perfect collateral—even when not explicitly collateralized. Thus, lending to customers does not adversely affect the firm's capacity to make other investments.

6 Final remarks

In our detailed invoice data set, the standard pecking-order hypothesis of trade credit can account only for a small fraction of the negative correlation between firms' creditworthiness and their payables. Most of the correlation arises because more creditworthy firms purchase less inputs, not because they pay suppliers earlier. By investigating the customers' account-

ing data we go on to find that more creditworthy firms employ considerably more labor compared to other inputs.

We show that these findings can be rationalized, both qualitatively and quantitatively, by adding labor input to the production function of the in-kind finance model of Burkart and Ellingsen (2004). As a firm becomes less creditworthy, the supply of bank credit diminishes and hence the firm will seek to borrow more from suppliers even if it requires using an inferior input mix. Thereby, we also identify the input mix as an indicator of financial constraints.

The model finally explains why trade credit is frequently offered with no explicit interest rate: Even sellers that are otherwise tightly financially constrained will be able to fully fund its receivables through loans from a well-informed lender.

An implication of the last finding is that only firms that lack such well-informed lenders need to charge their customers extra for the trade credit. With practices such as early payment discounts apparently vanishing from the scene, a natural direction for future research is to investigate why. Are more firms developing bank relationships? Or do modern supply chain finance practices, such as reverse factoring—where large customers help small suppliers to fund their receivables—substitute for suppliers' own bank relationships?

A final challenge for future research is to investigate the prediction of Proposition 1 empirically. If banks lend more money on the back of receivables than the “receivables secured lending” of about sixty to eighty percent that is frequently reported, how can we best measure the actual bank lending that trade credit causes?

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Internet Appendix A: Default

In this section, we consider theoretical issues relating to equilibrium default.

A1 Uncertainty and non-strategic default under imperfect competition

In this subsection, we neglect the possibility of strategic default in order to answer the following question: Will there be an impact of non-strategic default risk on the technology choice due to asymmetries in market power between input suppliers and banks?

The simplest possible case obtains when (i) there are only two states, one successful and one unsuccessful (bankruptcy), (ii) the probability of bankruptcy and the bankruptcy payoffs are both independent of the scale of the firm, (iii) the bank is competitive, and (iv) the capital input supplier is a price-setting monopolist.

Therefore, let the problem be the same as in Section 5, except $\phi = 0$ so strategic default is not a concern, and that there is a non-negative probability that the firm goes bankrupt, $(1 - h)$. As a result of the bankruptcy risk, both the bank and the input supplier have reason to change their prices. Under bankruptcy, the project returns a fixed amount f that will be too small to repay the debts; for concreteness, let the bank have the senior claim on this amount (in the absence of strategic default concerns, it ultimately does not matter who holds the claim). Since the supplier is now a price-setting monopolist, we need to introduce a variable to denote the supplier's cost, c (this can be production costs as well as interest costs.) We revert to the notation p for the supplier's price.

In order for a competitive bank to fund labor costs L , the repayment B in the non-default state must satisfy $L = hB + (1 - h)f$. Thus,

$$B = \frac{L - (1 - h)f}{h}.$$

Since the firm gets nothing in bankruptcy, the firm's problem is

$$\max_{K, L} h \left(K^\alpha L^\beta - B(L) - pK \right)$$

Using the first-order conditions and rearranging, the solution can be written

$$L^* = \alpha^{\frac{\alpha}{1-\alpha-\beta}} \beta^{\frac{1-\alpha}{1-\alpha-\beta}} h^{\frac{1-\alpha}{1-\alpha-\beta}} p^{\frac{-\alpha}{1-\alpha-\beta}},$$

$$K^* = L^* \frac{\alpha}{\beta} \frac{1}{hp}.$$

The next step is find p by solving the capital supplier's problem

$$\max_p K^*(p)(hp - c).$$

Using the first-order condition (and multiplying to get one of the exponents on p to be zero), we find the unique solution

$$p = \frac{1 - \beta}{h\alpha} c.$$

Note that the expected revenue per unit sold, ph , is independent of h and greater than the unit cost c (because $\alpha + \beta < 1$). In other words, the supplier effectively treats all customers the same. Default risk is neither subsidized nor penalized.

Finally, we can now compute the capital input cost share,

$$\frac{K^*}{K^* + L^*} = \frac{\alpha^2}{\alpha^2 + \beta(1 - \beta)c},$$

which is independent of the bankruptcy probability.

A2 Uncertainty and strategic default in the competitive model

We now extend our main (competitive) model to allow equilibrium default. To do so, it is convenient to start with the deterministic problem

$$\max_{K,L} Y(K, L) - \hat{p}K - L$$

subject to

$$L \leq B, \tag{A1}$$

$$Y(K, L) - \hat{p}K - L \geq \phi(B + \delta pK). \tag{A2}$$

Call this Problem STC (the simplified trade credit problem). This problem formulation takes for granted that capital input purchases are funded by suppliers. (By our previous analysis of Problem TC, we know that the solution to Problem STC will coincide with the solution of Problem TC for relevant ranges of parameters.)

Let us now add uncertainty to Problem STC. Specifically, suppose that there is ex ante uncertainty about what the value of ϕ will be; let $f(\phi)$ denote the probability distribution,

with support Φ . Let $r(K, L)$ denote the compensation for default risk that lenders require. For any triple (K, L, r) let $\hat{\phi}((K, L, r))$ denote the largest ϕ (not necessarily in Φ) for which the firm would not default, i.e., for which

$$Y(K, L) - (1 + r)(\hat{p}K + L) \geq \phi(B + \delta pK). \quad (\text{A3})$$

For any profit-maximizing choice of (K, L) , the left hand side is always non-negative and bounded, so there is always a unique solution $\hat{\phi}((K, L, r))$. Accordingly, let $\underline{\Phi}(K, L, r) = \{\phi \in \Phi | \phi \leq \hat{\phi}(K, L, r)\}$ and $\overline{\Phi}(K, L, r) = \{\phi \in \Phi | \phi > \hat{\phi}(K, L, r)\}$. The more general version of Program STC then becomes

$$\max_{K, L} \int_{\underline{\Phi}(K, L, r)} [Y(K, L) - (1 + r)(\hat{p}K + L)] f(\phi) d\phi + \int_{\overline{\Phi}(K, L, r)} \phi(B + \delta pK) f(\phi) d\phi$$

subject to

$$L \leq B, \quad (\text{A4})$$

$$(1 + r) \int_{\underline{\Phi}(K, L, r)} f(\phi) d\phi = 1, \quad (\text{A5})$$

where the second constraint ensures that the interest rate paid in the non-default states suffices for competitive risk-neutral lenders to be willing to participate. Call this Program TCU (trade credit under uncertainty).

Note first that when Φ is a singleton, Program TCU is identical to Program STC: The solution to UTC entails $\Phi = \underline{\Phi}$, for if $\Phi = \overline{\Phi}$ then (A5) is violated. Consequently, $r = 0$, and it remains to maximize $Y(K, L) - (\hat{p}K + L)$ subject to (A3) with $r = 0$.

Suppose next that there is some small probability that ϕ takes a considerably higher value, say ϕ' . In this case, it is inefficient to reduce (K, L) enough to deter diversion in all states. Instead, the optimal contract accepts that there will be default in state ϕ' , but increases r so as to compensate the lenders. As a result, K and L must fall somewhat in order to satisfy (A3). But if we increase the probability of ϕ' enough, the optimal solution instead is to reduce (K, L) until there is no default in any state. This example demonstrates that there does not have to be a monotonic relationship between the degree of credit rationing and the default probability. Is it a worrisome example?

We think not. If we instead confine attention to multiplicative transformations of a continuous function f , the relationship between the average ϕ and the default probability is increasing. The intuition is simple: Consider an upward shift in a continuous distribution $f_1(\phi)$

to a new distribution $f_2(\phi) = f(\nu\phi)$, with $\nu > 1$. Suppose there was a non-zero probability of default, say d , at the original solution $(K, L)^*$. Without any adjustment of (K, L) , the probability of default will now go up. Consider adjusting (K, L) down to the level $(K, L)'$ that gives the same default probability d as before. This cannot be optimal, because a slight upward adjustment of (K, L) generates a larger marginal return both in the no-default states (since marginal returns are decreasing) and in the default states. Thus, in the new optimum, the probability of default must be above d .

This argument, then, justifies using credit rating as a measure of the severity of financial constraints, just as in Besley, Roland and Van Reenen (2020).

Internet Appendix B: Details on data and sample construction

B1 Sample construction

The initial contract data set contains 34.0 million contracts issued by 59 suppliers to 250,094 customers over the sample period 2005–2008. We apply the following sample selection screens to construct the final sample. Firstly, the credit bureau required us to secure written consent from each of the suppliers in order to use the data for research purposes; one supplier did not agree and is therefore excluded from the sample. Secondly, we drop firm-years for which financial accounts data is unavailable, which is primarily for banks, insurance companies, and non-incorporated firms. Thirdly, we drop observations for which one or several variables are likely to suffer from measurement error.^{B1} Fourthly, we drop observations belonging to customer-supplier years in which the total trade value is below 1,000 SEK (roughly 125 USD). Fifthly, we drop the remaining financial firms in the sample. Sixthly, we drop inactive firms, defined as observations for which annual sales are less than 100,000 SEK, or the number of employees is zero. Finally, we drop observations with missing values for one or several variables, as well as observations that belong to singleton groups in the baseline specification. Applying these sample screens leaves us with a final sample consisting of 21.0 million trade credit contracts, issued by 46 suppliers to 126,488 unique customers over the four-year sample period 2005–2008. Table B1 shows in detail how the sample size changes with the application of each sample selection screen.

^{B1}These are contracts for which the amount to be paid exceeds the buyer's total input costs or the seller's total revenue for the year, as reported in their respective financial accounts; contracts where measured days to payment is negative; and contracts in which the agreed maturity exceeds 180 days. The latter are not obviously cases of measurement error, but contracts with agreed maturities exceeding six months are nevertheless large outliers, which motivates dropping them from the sample.

Table B1: Sample construction

	Suppliers	Customers	Contracts
1. Initial sample: All contracts	59	250,094	33,954,077
2. Keep suppliers that gave permission to use data	58	248,798	33,914,846
3. Drop firm-years without financial accounts	55	185,902	29,076,117
4. Drop anomalous contracts	54	180,595	27,449,778
5. Drop match-years with total trade value below 1,000 SEK	54	169,363	27,220,063
6. Drop remaining financial firms	47	150,044	23,665,143
7. Drop firm-years with annual sales less than 100,000 SEK	47	145,034	23,452,003
8. Drop firm-years with no employees	47	136,746	22,728,995
9. Drop observations with missing values	47	132,131	22,453,378
10. Drop observations that are singleton in baseline	46	126,488	20,982,287
Final sample	46	126,488	20,982,287

This table shows how the size and composition of the sample change with each of the sample selection screens described in Section B1.

B2 Defaults on sample contracts

Our contract dataset comprises records of completed trade credit transactions—transactions for which the supplier has received final payment from the customer—but does not include contracts on which the buyer has defaulted. To assess the extent to which missing contracts due to defaults may be a problem for our analysis, we make use of a data set from the Swedish Enforcement Agency, which consists of all trade credit defaults reported by suppliers between 2005 and 2008.^{B2} For each supplier-customer pair and year during the sample period, we compute the ratio of the default amount recorded by the Enforcement Agency to the total transaction value during the year, defined as the sum of the amount of defaulted debt and the total value of all completed contracts. We find that only 0.32 percent of the customer-supplier pairs in our sample have non-zero default amounts in a given year and that defaults on average make up 0.07 percent of the total annual transaction value, which suggests that missing contracts due to defaults are quite infrequent and thus unlikely to be of concern for the analysis.

It should be noted, however, that this exercise cannot account for defaults that suppliers

^{B2}The Swedish Enforcement Agency (*Kronofogdemyndigheten*) is a public authority that coordinates the administrative process of bankruptcy resolution in Sweden. It is also responsible for administering the collection of private and public debt, and in this capacity provides legal support to suppliers for the management of their unsettled trade credit claims.

choose not to report to the Enforcement Agency; it is therefore conceivable that the true level of trade credit defaults is somewhat larger than our analysis suggests. On the one hand, sellers have a strong incentive to report trade credit defaults to the Enforcement Agency, since this is needed to establish a claim on the bankruptcy estate of a failed buyer. On the other hand, sellers may be discouraged from doing so by the fact that the Swedish Bankruptcy Act provides trade credit with junior priority status, which means that their chances of recovering claims on failed buyers' bankruptcy estates are very low (Thorburn, 2000). It is clearly the case, however, that a seller's incentive for reporting a default is increasing in the size of the transaction on which the buyer has defaulted, so it is likely that primarily small-sized defaults go unreported.