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Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis*

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Abstract

Using an exhaustive data set on claims held by trade creditors (suppliers) on failed trade debtors (customers), we quantify the importance of trade credit chains for the propagation of corporate bankruptcy. We show that trade creditors experience significant trade credit losses due to trade debtor failures and that creditors' bankruptcy risks increase in the size of incurred losses. By exploring the roles of financial constraints and creditor-debtor dependences, we infer that the trade credit failure propagation mechanism is driven by both credit losses and demand shrinkage. Finally, we show that the documented propagation mechanism constitutes a significant part of the overall bankruptcy frequency, suggesting that it has measurable implications for the aggregate level.

Keywords: Trade credit; Credit chains; Bankruptcy; Contagion

JEL: G30; G33

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1 Introduction

Theory predicts that trade credit chains make up a channel through which liquidity shocks are propagated in the economy: Kiyotaki and Moore (1997) provide the seminal contribution.[1] A trade credit debtor (customer) in bankruptcy will almost surely default on the claims held by its trade creditors (suppliers), and thereby invoke credit losses. Such credit losses could, in turn, push the trade creditors into insolvency and subsequent bankruptcy. Thus, trade credit chains are potentially an important mechanism through which corporate failures are propagated in the economy. Moreover, the trade credit failure propagation mechanism may also play a wider role by amplifying the impact of idiosyncratic shocks towards persistent effects on aggregate output.[2] However, although trade credit chains are likely to propagate corporate failure and generate aggregate effects, there is hitherto no empirical work that directly examines the trade credit failure propagation mechanism, most likely due to data limitations on trade credit chains.[3]

Our contribution is empirical and explores the importance of trade credit chains for the propagation of corporate failures. To this end, we have compiled a vast Swedish data set containing information on all corporate bankruptcies and associated trade credit claims. The richness of the data provides an opportunity to empirically gauge the risks associated with trade credit issuance and failure, conditional on precise creditor and debtor characteristics. We begin by relating creditor issuance of trade credit to the credit losses incurred in trade debtor failures, and thereby establish and quantify the credit risks involved in trade credit. We then move on to a comprehensive characterization of the bankruptcy risk that trade debtor failures impose on trade creditors—with a focus on credit loss effects for creditor failure risk. The latter provides direct inference on the propagation mechanism in trade credit chains for corporate failure contagion. Finally, we show that the documented propagation mechanism gives rise to measurable aggregate effects.

We face several challenges in modelling the link between debtor failure and enhanced creditor risk. It is intuitive to consider two direct effects: the credit loss on the one hand, but invariably also a loss of future business opportunities with the failed debtor, that is, a demand effect. The two channels consti-

[1] More recent contributors include Cardoso-Lecourtois (2004), Boissay (2006), and Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2008), who evaluate the role played by trade credit default propagation, and—closely related—Allan and Gale (2000) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) who study contagion of counterparty risk in financial networks.

[2] Kiyotaki and Moore (1997) suggest ".. a small, temporary shock to the liquidity of some firms may cause a chain reaction in which other firms get into financial difficulties, thus generating a large, persistent fall in aggregate activity." Scrutinizing this prediction, Raddatz (2010) empirically shows that an increased use of trade credit—linking two industries together—results in a higher output correlation between the industries. More generally, Gabaix (2011) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) propose that the propagation of idiosyncratic shocks through inter-firm linkages have macroeconomic relevance—in contrast with conventional wisdom dictating that shocks at the firm-, or sector-level, will cancel out in the aggregate, i.e., the diversification argument.

[3] To this date, there exists survey and indirect evidence on the importance of the propagation mechanism. Recent survey evidence—for US firms—lists non-payments by trade debtors as the prime cause of financial distress and bankruptcy (see Bradley and Rubach 2002). Hertzel, Li, Officer, and Rodgers (2008) show that suppliers of goods to financial distress firms experience negative stock price returns around the distress date. Boissay and Gropp (2012) document that firms are likely to postpone their own trade credit payments as a response to late payments by their trade debtors. Jorion and Zhang (2009) study trade credit relationships with respect to counterparty risk effects.

tute the trade credit failure propagation mechanism, henceforth labeled as the propagation mechanism. Moreover, in characterizing the propagation mechanism one can think of three, potentially important, confounding factors that play roles. The first one is common shocks that hit firms operating in the same industry, or region, that can spuriously exaggerate the significance of trade credit relationships between counterparties with respect to their failure outcomes. The second one concerns selection through endogenous matching of counterparties of low quality, which likewise attributes too much weight to trade debtor failures for creditor failure risk. The third confounding factor is one of reverse causation; due to a contraction in trade credit supply the failing creditor causes a debtor failure, rather than the other way around. We therefore carefully rig our empirical analysis to account for the influences of common shocks, endogenous matching, and reverse causality.

The empirical analysis is conducted on a data set for the universe of Swedish corporate firms in the period 2007–2011, and based on their yearly financial statements. In addition, we have acquired precise information on trade creditor and debtor identities (using the 10-digit unique, corporate identifier) and characteristics from a trade credit perspective, including their respective bankruptcy dates, and the size of the claims involved. Thus, we know whether a firm, in its role as a trade creditor, experienced a trade debtor failure, when the failure happened, and how large the credit loss was. For a much longer sample period, 1996–2011, we have all of the above information but the debtor identities. Sacrificing information on the size of the creditor claims in debtor bankruptcies (and debtor identities) extends the sample period to 1992–2011. In total, for the extended period, our data set contains around 318,000 firm-year observations on trade creditors that experienced one, or several, trade debtor failures.

Our results show that trade credit issuance is associated with significant credit losses. At the aggregate level, yearly credit losses incurred by Swedish trade creditors are roughly 50 percent larger than the credit losses incurred by Swedish banks in their lending to non-financial firms. Thus, corporate failures impose substantially larger credit losses on the corporate sector than on the banking sector. At the firm level, controlling for creditor characteristics, we show that a $100 increase in the amount of outstanding trade credit is associated with an increase in yearly trade credit losses of around $8.[4] Furthermore, controlling for creditor characteristics, we find that trade debtor failures are associated with substantially enhanced bankruptcy risks for the involved trade creditors. The estimated average marginal effect implies an increase in annual creditor failure risk by around 0.8 percentage points when exposed to a debtor failure. In comparison with the average unconditional annual failure risk of 1.5 percent, facing a trade debtor failure is thus associated with an increased creditor failure risk of 53 percent at the mean. We also show that creditor failure risk is strongly related to the size of trade credit losses.

[4] Based on data for the period 2004–2008, the credit bureau Upplysningscentralen AB provided an estimate of the average time to payment for trade credit contracts in Sweden of 31.5 days. Thus, our estimate implies that trade creditors on average incur credit losses of ($8/12 months =) 67 cents for each $100 of issued trade credit.

We show that the above effects persist when we account for common shocks and endogenous matching by saturating our models with combinations of time-, industry-, location-, creditor- and debtor-fixed effects. By conditioning on relative creditor to debtor size—and thereby, on implied creditor importance—we also show that the documented effects are negligible for debtor failures for which creditors are relatively large and important providers of credit; mitigating concerns for our findings being driven by a reverse causal relationship—downstream rather than upstream contagion. Throughout, our results are thus consistent with the notion that trade debtor failures impose an increased failure risk on affected trade creditors.

To evaluate the relative importance of credit versus demand losses, we explore whether financially constrained creditors are more exposed to trade credit failures. Kiyotaki and Moore (1997) propose that financially constrained creditors are more exposed to the trade credit losses imposed by failed trade debtors. Accordingly, based on an exogenous determined industry classification of creditors' external financing and liquidity dependence, and creditor characteristics related to borrowing capacity and liquidity, we find that creditors that are more financially constrained are more exposed to trade credit losses. However, we also find that the propagation mechanism is enhanced in *R&D* intense industries where supplier-customer relationships are expected to be more important, i.e., industries where creditors are involved in the production of specialized goods and services making them potentially more vulnerable to shortfalls in demand. To reconcile these two effects, we apply model specifications that exploit the imperfect correlation between the credit loss and the demand loss components. That is, a debtor failure may impose a large trade credit loss on a creditor, even if the debtor only accounts for a small fraction of the creditor's annual sales. When simultaneously controlling for both channels, we find that the increased creditor risk associated with a debtor failure is driven by both credit losses and declines in demand, and possibly a combination of the two.

Finally, our data set covers the universe of Swedish corporate firms which allows us to use our micro-econometric models to quantify the contribution from the propagation mechanism to the overall, yearly bankruptcy frequency. We find that the propagation mechanism explains a significant part of the aggregate bankruptcy frequency, especially during economic downturns. More specifically, we show that the propagation mechanism increased the overall bankruptcy frequency by around 13 percent during the Swedish banking crisis in the early 1990's. Thus, we find support for the presumption that the propagation mechanism in trade credit chains amplifies the impact of idiosyncratic shocks to the aggregate level.

Our paper is related to Boissay and Gropp (2013). They use similar data to document that trade creditors are likely to respond to late trade debtor payments by, in turn, postponing their own trade credit payments. A negative liquidity shock is shown to be transmitted along the trade credit chain until it reaches a trade creditor with access to external financing, or sufficient cash-holdings, in order to absorb the liquidity shock. Their result suggests that trade credit chains function as an insurance mechanism by allocating liquidity from unconstrained to constrained firms, in line with the predictions by Wilner (2000) and Cuñat (2007). Our paper—in contrast—highlights the dark side of trade credit by providing insights on its role as propagator of corporate failure. Unlike late payments, debtor bankruptcies invoke permanent losses on creditors—recovery rates are typically negligible—which means that shocks propagated by this mechanism can only have detrimental effects. The Great Recession has shown that corporate failures are of fundamental importance for financial stability through their effects on banks and financial markets, as well as output growth and employment, suggesting the urgency for a better understanding of failure determination.

Another closely related paper is that by Jorion and Zhang (2009). They make use of a sample of around 250 US corporate bankruptcies and the subset of the associated, unsecured creditors holding the largest claims on the bankrupt debtors. Their analysis shows that trade creditors with large exposures on average exhibit an increased distress risk (measured by creditor delisting, and rating downgrade) in the years following a debtor failure. Our paper contributes to their work by exploring a substantially more comprehensive data set which allows us to rig an empirical analysis that more carefully controls for the impact of confounding factors. In particular, we attempt to describe the two channels underlying the propagation mechanism, stemming from trade credit losses and demand shrinkage. Moreover, our analysis goes beyond existing work by exploring important cross-sectional determinants of the propagation mechanism and by showing its relevance at the aggregate level.

A somewhat more general take on the importance of the propagation mechanism is (indirectly) suggested by Das, Duffie, Kapadia, and Saita (2007). They ask the question why corporate defaults cluster in time, and note that one candidate explanation is default contagion. Das et al. empirically test whether there is evidence for an excess default correlation, over and above that implied by the correlation of firms' risk factors determining their conditional default probabilities. Their tests are, in general, rejected for models that take into account idiosyncratic, as well as common risk factors, but do not consider contagion per se. Our results suggest that trade credit shocks capture default contagion and could well be the missing link explaining corporate failure clustering.

The remainder of this paper is structured as follows. The next section presents a conceptual framework and the empirical approach that we will pursue. Section 3 details our data resources, the institutional setting, and provides some descriptive statistics. The empirical analyses and results are described in Section 4. We will first address the relationship between trade credit issuance and the credit losses imposed by trade debtor failures and then tackle bankruptcy risks for trade creditors imposed by trade debtor failures, and also examine cross-sectional determinants of these risks, as well as implications for the aggregate level. Section 5 concludes.

2 Conceptual Framework and Empirical Approach

Our empirical analysis rests on a conceptual framework that centers on three hypotheses: we postulate that trade credit issuance involves important credit losses, that these trade credit losses are associated with bankruptcies that propagate along the trade credit chains, and that the propagation mechanism generates measurable effects at the aggregate level.

2.1 Testable hypotheses

A strand of the theoretical literature on trade credit suggests that trade creditors have a competitive edge over other financial intermediaries in their ability to assess prospective debtors' credit worthiness and their ongoing activities (see, e.g., Smith, 1987; Biais and Gollier, 1997; and Burkart and Ellingsen, 2004). A superior monitoring ability, in combination with typically short-term maturity, will thus allow trade creditors to—in good time—adjust their credit supply to distressed debtors and thereby cap the credit losses associated with trade credit issuance. However, another strand of the theoretical literature proposes that rents from ongoing relationships incentivize trade creditors to further support distressed debtors by not invoking called-for reductions in the amounts of trade credit issued (see Wilner, 2000; and Cuñat, 2007). Thus, it is an empirical question whether, or not, trade credit issuance is associated with non-negligible credit losses, motivating the following testable hypothesis:

Hypothesis 1. *Trade credit issuance is positively associated with credit losses.*

As noted above, theoretical research argues that a trade debtor failure may cause its trade creditors, in turn, to fail. One can think of two direct channels through which trade debtor failures yield enhanced bankruptcy risks for creditors. Firstly, the trade credit losses may drive creditors into failure, either by causing a sufficiently severe shortage of liquid funds (cash-flow-based insolvency), or through a reduction in creditor assets such that they are exceeded by the liabilities (balance-sheet-based insolvency), or possibly through a combination of the two. Secondly, a debtor failure shrinks its creditors' downstream markets. The decline in demand for the creditors' goods decreases the value of their assets and therefore imposes an increased bankruptcy risk. The first propagation channel is due to the existence of trade credit chains, whereas the second propagation channel is more general and may be present irrespective of trade credit links. Both channels are potentially important for the propagation of corporate failures.[5] The

[5] The relative importance of two channels depends on the financial position of the creditor and the fraction of the creditor's ongoing sales that is directed towards the failed debtor. On the one hand, a debtor failure may lead to a bearable decline in a creditor's downstream market, but the related credit loss may be sufficiently large to push the creditor into insolvency and

trade credit loss channel has—as of yet—not been empirically documented. In doing so, one must take account of the ever-present demand channel, and provide evidence of effects from trade credit losses on creditor failure separate from effects induced by demand shrinkage. This leads us to our second testable hypothesis:

Hypothesis 2. The trade credit losses arising in trade debtor failures impose increased trade creditor failure risks.

In demonstrating that debtor failures induce an increased creditor failure risk, we need to consider three possible confounding circumstances. Firstly, debtor and creditor failure could be correlated events due to a common shock that simultaneously hit firms that are connected not primarily by their trade credit arrangement, but by belonging to the same industry, or by sharing geographic location. Secondly, we must also allow for the possibility of selection effects through endogenous matching. Suppose that both creditor and debtor firms ending up in bankruptcy are low-quality firms. This may occur when low-quality customers are apt to source their inputs from low-quality suppliers, or when low-quality suppliers are pressed by competition to target low-quality customers. Such matching outcomes can be described as being static in the sense that inherently bad creditors are matched with inherently bad debtors. However, more interesting and challenging is to consider potential matching of a dynamic nature, where the quality of the creditors and debtors changes over time and therefore yields also time-varying matching outcomes. If creditors and debtors belong to a shrinking industry, then an omitted factor (industry shrinkage and exit of low-quality firms) may spuriously boost the causal link between debtor failure and subsequent creditor failure. It is plausible that dynamic matching is positively associated with firm distress and subsequent failure. As a firm enters into distress—and its trading partners can observe this—the need to re-match arises; and the more aggravated distress there is, the stronger the signal, and the greater the need to re-match. Thirdly, although Hertzel, Zhi, and Rodgers (2008) empirically document that the dominating contagion effect goes upstream—from debtors to their creditors—and not downstream, we nevertheless need to contemplate a reverse relationship underlying a positive correlation between creditor and debtor failures, i.e., that creditor failures cause debtor failures. This would be the case if distressed and subsequently failing creditors contract trade credit supply to their customers, and the credit contraction causes the debtors to fail. We carefully rig our empirical analysis to account for these potentially confounding circumstances.

Finally, for completeness, it is reasonable to investigate whether the propagation mechanism is quantitatively important at the macro level. As noted above there are recent contributions suggesting that

subsequent bankruptcy. On the other hand, the credit loss that a debtor failure imposes on a creditor may not lead to insolvency, but nevertheless yields a sufficiently large decline in overall, future demand for the creditor's goods, such that it will ultimately fail. Thus, there are potentially cases where the credit loss channel outweighs the demand channel, and vice versa. In addition, the two channels are likely to reinforce each other.

idiosyncratic shocks in production networks do not cancel in the aggregate due to propagation effects through inter-firm linkages, c.f. Gabaix (2011) and Acemoglu et al. (2012). Gabaix emphasizes skewness in the firm size distribution as a driver of idiosyncratic shock propagation, i.e., small shocks hitting large firms will be amplified to influence macro outcomes, whereas small shocks hitting small firms will not—they cancel. Acemoglu et al. argue that an intersectoral network of firms in the economy plays a similar role and predict that: "shocks to sectors that take more central positions in the intersectoral network have a disproportionate effect on aggregate output." Another strand of the literature, closely related to our work, highlights how idiosyncratic shocks are propagated in financial networks, potentially causing cascades of defaults and systemic failure. In a seminal paper Allan and Gale (2000) show that financial networks that are more interconnected are more resilient to idiosyncratic shocks. However, more recent work by Acemoglu et al. (2015) moderates our understanding of contagion in financial networks by demonstrating that more interconnected networks exhibit stable properties in some states of the world, but may—if shocks are sufficiently large, or many—exacerbate financial contagion in other states. In our framework an analogy would be that idiosyncratic shocks—trade debtor failures—hitting firms in trade credit chains may lead to amplification towards aggregate effects, as originally suggested by Kiyotaki and Moore (1997). Our third and final hypothesis therefore reads:

Hypothesis 3. *The trade debtor failure induced propagation mechanism generates measurable aggregate effects.*

By exploring bankruptcy propagation along the intensive margin, we may well understate the overall contagion effect in trade credit chains. As an example, consider the extensive margin effect arising when a debtor failure will drive its creditors into distress, but not bankruptcy. These creditors may, in turn, and due to distress, cancel trade credit payments to their creditors; and for a sufficiently large late payment, a creditor of the original creditor may fail. Bankruptcies can thus propagate along the trade credit chain both through the intensive and extensive margins. The results reported in this paper with respect to the intensive margin can therefore be interpreted as a lower bound for the importance of trade credit chains for bankruptcy propagation.

2.2 Empirical approach

The foremost distinguishing feature of our data is that we observe the universe of trade credit claims that Swedish trade creditors held on bankrupt trade debtors. It is therefore straight forward to empirically evaluate Hypothesis 1 by estimating models that capture the degree of association between trade credit losses and issuance. In these Tobit regressions—on account of losses being non-negative—we control for creditor characteristics that the empirical literature has shown to be important determinants of trade credit issuance, as well as a set of fixed effects to control for variation in trade credit issuance and losses that is due to time, industry belonging, and geographical location.

The empirical basis for evaluating Hypothesis 2 is estimation of the conditional probability that a trade creditor fails due to a trade debtor failure. Given the structure of our data, a multi-period logistic regression model is a natural framework to estimate creditor failure probabilities.[6] However, an unfortunate consequence of including a very large number of fixed effects in the logistic model is that the model becomes partly unidentified; there is no maximum likelihood estimator for the fixed effect parameters corresponding to groups for which we do not observe any bankruptcies, or, less likely, for groups where we only observe bankruptcies (c.f. Heckman and MaCurdy, 1980). In our strictest specifications—saturated with fixed effects—we therefore use a linear probability model (LPM).[7]

We propose to measure the average impact of a debtor failure on the involved creditors over all links in the observed trade credit chains.[8] Throughout the empirical analysis we will use two alternative right hand-side variables to capture the risk that debtor failures impose on their creditors. Firstly, by conditioning on a dummy variable indicating whether, or not, a creditor experienced a debtor failure. Secondly, we will measure the shock by the size of the creditors' claims held on the failed debtor (normalized by creditor assets) to closer capture the economic severity of the event.

Our baseline model incorporates creditor characteristics that have been shown to be important determinants of firm failure, such as capital structure, cash and liquid asset holdings, profitability, size, and age (see, e.g., Shumway 2001; Campbell, Hilscher, and Szilagya, 2008; Jacobson, Roszbach, and Lindé, 2013; Giordani, Jacobson, von Schedvin and Villani, 2014). Financial ratios in accounting data are typically, for given firm, highly persistent over time, which may introduce bias in variance estimates. To correct standard errors for such persistence they are clustered at the firm level (c.f. Petersen 2009). Moreover, the baseline specification includes credit rating-, time-, industry-, and location-fixed effects to account for creditor quality, business cycle fluctuations, cross-industry and cross-location heterogeneity, respectively. These control variables are retained for all subsequent specifications.

As a first step, we have to establish that a trade debtor failure event imposes an increased bankruptcy risk on the trade creditors. The increased failure risk could be due to an incurred credit loss, or to a decline in demand, or possibly—even likely—to a combination of the two, that is, what we refer to as

[6] Creditor failure probabilities are ultimately articulations about creditors' life spans, or durations, suggesting statistical survival analysis as the appropriate framework for inference. The likelihood function for the multi-period logistic model and a discrete-time survival model, with the hazard probability given by the logistic function, are identical (for an explicit account see Shumway (2001)). Hence, estimation of a logistic model is tantamount to that of a discrete-time hazard model.

[7] Choosing between the logistic model and the LPM introduces a trade-off. On the one hand, as compared with the logistic model, the LPM allows for the inclusion of fixed effects beyond the point disabling identification in the logistic model. On the other hand, the LPM imposes heteroskedasticity, and also the probability estimates are not bounded by the unit interval. We deal with the former problem by calculating heteroskedasticity-consistent standard errors. An intuitively appealing approach to evaluate the performance of the LPM suggested by Wooldridge (2002, p. 455) is to compare the LPM-estimates with the average marginal effects obtained for the logistic model, under the baseline specification for which both models are identified.

[8] That is, for our baseline results we do not condition the estimated effects on the creditor-debtor link position in the trade credit chains. However, we will also report results from a model that distinguishes between first- and higher-order effects, i.e., the specification conditions on whether a failing debtor, in turn, also had experienced a debtor failure.

the propagation mechanism. However, at this stage, we first need to make sure that the enhanced creditor risk is not spuriously driven by common shocks, endogenous matching, or by a reverse relationship, as noted above.

We first tackle the concern that the increased creditor failure risk induced by a trade debtor failure is in fact a spurious correlation due to a common shock that simultaneously affects both the trade debtor and his creditors. To fix ideas, consider two firms—a supplier and his customer—located in the same city and operating in the same industry. Suppose a shock, say a cost-push shock, simultaneously hit them and is severe enough to fail them both. Then the debtor failure may appear to cause the creditor failure when in fact the failure events are outcomes of the common shock. Our strategy to control for common shocks is two-fold. Firstly, we estimate our baseline model augmented by a triple-interaction between time-, industry-, and location-fixed effects. The triple-interaction controls for the impact of observed and unobserved time-varying shocks that are common to firms operating within a specific industry and region. Identification is thus obtained by comparing failure risks for creditors which were, or were not, exposed to debtor failures, but have in common that they operate within the same industry and the same region in a given year. Alternatively, under the same setting, we can compare differences in creditor failure risks from variation in claims-size exposures to failed debtors. Secondly, we apply a version of the model augmented with debtor-fixed effects. The debtor-fixed effects control for observed and unobserved debtor characteristics at the point in time of the debtor failure. Identification now resides in comparing failure risks for different creditors holding trade credit claims on the same failed debtor. It is unlikely that a common shock simultaneously hitting a creditor and debtor is correlated with the amount of credit issued by the creditor to the debtor. Thus, it follows that results obtained from models controlling for debtor-fixed effects should not be influenced by common shocks. Nor should results in such a setting be driven by the presence of static endogenous matching stemming from inherently bad debtors.

In a similar fashion, we can account for static endogenous matching on the creditor side—high-risk creditors serving high-risk debtors. For this purpose, we augment the linear probability model with creditor-fixed effects, controlling for observed and unobserved time-invariant creditor characteristics, and achieve identification by comparing creditor failure risks for a given creditor to variation in debtor failure exposures over time. Thus, the creditor-fixed effects specification eliminates any bias due to trade debtor failures being clustered along the firm-years of creditors that subsequently fail for other reasons than the debtor failure. However, as noted in the previous section, the endogenous matching may be of a dynamic nature, i.e., resulting from shifts in creditor and debtor quality over time, and in particular, when trading partners enter into distress. Time-varying creditor quality is dealt with by including credit rating-fixed effects in all estimations, and by estimating models using sub-samples of high-quality creditors.[9] Finding a positive relationship between creditor and debtor failures also for samples of low-risk creditors, extenuate worries of confounding effects from dynamic matching. Likewise, we will consider the credit quality of the debtor prior to its failure, and by conditioning the analysis on debtor riskiness, we wish to demonstrate that enhanced creditor risk is not driven by failures of low-quality debtors.

Yet another empirical challenge arises from the possibility of a reversed causal relationship—downstream contagion, rather than upstream—potentially introducing biases and erroneous conclusions. However, the structure of our data set mitigates this concern, at least in part. More specifically, if it were the case that a creditor withdraws its trade credit supply to a debtor, and this credit withdrawal subsequently causes the debtor to fail, then we will obviously not observe any claims held by this creditor on the failed debtor, i.e., such events are not captured by the data. Nevertheless, it may well be that a creditor only partly contracts its supply; not altogether, but sufficiently much to fail the debtor. Such cases would show up in our data, and we propose to assess their importance on the basis of the following presumption. Cases of contracted credit with dire consequences for the debtors should intuitively involve large creditors extending sizeable shares of debtors' accounts payable, i.e., cases where the creditors are more likely to be important providers of trade credit from the debtor perspective. By analyzing sub-samples of relatively large creditors to small debtors, we provide ample opportunity for an downstream contagion mechanism to manifest. That is, to the extent downstream contagion underlies failure correlation, we should expect an enhanced correlation when the debtors are substantially smaller than the creditors. The reasoning underlying this approach is supported by descriptive statistics showing that relative larger creditors on average provide a larger share of the total amount of trade credit claims held on failed debtors.

In the next step, we will focus the analysis on the two direct risk drivers—credit losses and demand shrinkage—to get to the heart of Hypothesis 2. The challenge is to separately tease out both the credit loss effect and the demand loss effect; we therefore propose a series of specifications in which the two channels are simultaneously borne out by the data. When considered jointly, these models should provide compelling evidence for the existence of a trade credit loss channel affecting creditor failure risk such that changes in demand conditions cannot credibly account for, and vice versa. Thus, we will consider, in turn; external financing dependence, liquidity dependence, general demand dependence, and debtor-specific demand dependence.

Kiyotaki and Moore (1997) propose that financially constrained firms should be relatively more exposed to the liquidity shortfall due to the credit losses invoked by trade debtors' failures. Relatively more exposed than non-constrained firms, and relatively more to shortfalls in liquidity than in demand.

[9] The credit ratings range between 1 (high risk) and 5 (low risk) and are assigned—partly by means of automated model support—by the largest Swedish credit bureau, UC, on a continuous basis, and whenever new information is available.

To explore this prediction we adapt two exogenous measures of financial constraints: the Rajan and Zingales (1998) measure of external financing dependence and the Raddatz (2006) measure of liquidity dependence. The two measures are calculated on public US firm-level data and give characterizations of various industries' relative external financing and liquidity dependence, respectively. Rajan and Zingales argue that financial markets in the US are among the most advanced in the world and for US public firms in particular there should be an unrestricted supply of external financing available; hence any differences across industries should be driven by the dependence on external financing and liquidity needs. The US industry classification then provides a truly exogenous measure that can identify differences in financing and liquidity dependencies across industries in other countries.

We calculate the external financing dependence and liquidity dependence industry classifications using longer and updated Compustat data, and extend them to cover all industries. More specifically, we calculate the two measures based on a sample of public US firms obtained from Compustat for the period 1990–2009.[10] The external financing and liquidity dependence classification are calculated at the two-digit SIC-level and the codes are then translated into SNI-codes (Swedish industry codes) in order to apply them to the firms in our sample.

In addition, we complement the analysis based on the exogenous classification by exploring additional, more direct, creditor characteristics related to borrowing capacity and liquidity holdings. In sum, empirical results showing that the risk that trade debtor failures impose on trade creditors is enhanced for credit and liquidity constrained creditors support the notion that credit losses in trade credit chains matter for the propagation of corporate failures, consistent with Hypothesis 2.

We next propose to explore heterogeneity in the propagation mechanism that can be attributed to the demand channel. More specifically, Hertzel et al. (2008) suggest that firms producing specialized goods, as measured by *R&D* expenditures, are more exposed trade creditors. They argue that such firms are more dependent on long-term supplier-customer relationships. Hence, the debtor failure for creditors that produce specialized goods should be more severe in the demand-loss dimension. Exploring trade debtor failures' effects on trade creditors operating in *R&D* intensive industries should therefore provide insights on the relative importance of the demand shocks. The *R&D* intensity measure is calculated as the total amount of *R&D* expenditures scaled by the total amount of net sales for firms with more than 10 employees.[11]

[10] The external finance (EFD) and liquidity dependence (LD) measures are calculated at the firm-level, over the period 1990 to 2009, by first summing capital expenditures (CAPX), cash flow from operations (CF), sales (S), and inventories (INVT). We then calculate the EFD for each firm as (CAPX $-$ CF)/CAPX and LD for each firm as INVT/S. CF is defined as the sum of cash flow from operations (OANCF) plus decreases in inventories (INVT), decreases in receivables (RECT), and increases in payables (AP). Only mature firms in existence for more than 10 years are included. The industry classification is then obtained by the median firm EFD and LD in each two-digit SIC industry.

[11] Our measure on $R\&D$ intensity is constructed using firm-level data from Statistics Sweden on $R\&D$ expenditures and net sales in 2009. The measure spans between 0 and 18 percent. The Real Estate Service Sector (SNI: 68, and 77-81) comes out as the least $R\&D$ intensive industry and the most intensive is the Computer Manufacturing Sector (SNI: 26).

In alternative specifications, we will consider the importance of debtor-specific demand relative to total demand for creditors' goods and services. To this end, we will exploit the substantial variation in the asset-turnover-ratio, $Sales/Assets$, for the firms in our sample, to evaluate the impact of credit losses while holding demand losses constant. The idea is that a debtor failure can impose a large trade credit loss on a creditor, even if the debtor only makes up a small fraction of the creditor's annual sales.[12] By simultaneously controlling for both trade credit losses and demand shrinkages, we are attempting to rig an experiment that demonstrates the quantitative importance of both channels—thus providing further evidence in support of Hypothesis 2.

In a final exercise, we will evaluate Hypothesis 3 and the question whether the propagation mechanism is important at the aggregate level. To this end we make use of the fact that our data cover the population of Swedish corporate firms and examine how the presence—and absence—of the propagation mechanism in an estimated micro-econometric model alters predicted, yearly outcomes of the aggregate bankruptcy frequency in Sweden.

3 Data, Institutional Setting, and Descriptive Statistics

In this section we first outline the data that we explore in the empirical section and describe the institutional setting with a focus on the Swedish bankruptcy code. We then proceed by providing descriptive statistics that highlight the risks that trade debtor failures impose on trade creditors.

3.1 Data and institutional setting

From the leading Swedish credit bureau, Upplysningscentralen AB (UC), we have obtained records of corporate firm bankruptcies for the period 1992–2011. According to the Swedish bankruptcy code, the firm itself, or any individual creditor can file for bankruptcy.[13] The bankruptcy application is filed to a district court, which will initiate the bankruptcy procedure if the firm is deemed insolvent, and if it is highly unlikely that the firm will recover within a near future. If the court approves the bankruptcy filing then control rights are immediately transferred from the firm's management to a court-appointed

[12] A simple example will illustrate how the asset-turnover-ratio, $Sales/Assets$, can proxy for debtor-specific demand. Consider the case where a debtor fails and two creditors are affected. We assume that all goods are sold on credit and that the monthly sales are equal over the year. Both creditors have the same amount of yearly sales, 120 units, and experience a credit loss of 1 unit due to the debtor failure. However, the asset-turnover-ratio is 0.2 for one of the creditors and 4 for the other (these values correspond to the 10^{th} and 90^{th} percentiles in the $Sales/Assets$-distribution, see Table 1). This implies that both creditors experience an equally sized demand loss corresponding to (1×12 months $/120 =$) 10.0 percent of yearly sales. However, the discrepancy in the asset-turnover-ratio entails that the creditor with a ratio of 0.2 makes a credit loss of ($1/600 =$) 0.2 percent of total assets whereas the other creditor makes substantially larger losses of ($1/30 =$) 3.3 percent.

[13] See Thorburn (2000) for a comprehensive overview of the Swedish bankruptcy code. In 2013, according to statistics obtained from the Swedish Enforcement Authority (Tillsynsmyndigheten i konkurs), a total of 8,065 applications for bankruptcy were filed in Sweden, and a vast majority of these concerned corporate firms. 73 percent were filed by the subsequently failing firm itself; another 21 percent of filings came from the tax authorities; and the remaining 6 percent are categorized as filed by "others". The latter is dominated by banks and other financial firms.

trustee. The trustee continues the bankruptcy process by constructing an inventory of the firm's assets and liabilities. The assets are then auctioned off and the creditors' claims are covered according to absolute priority rights, and with no priority deviations being allowed. According to the absolute priority rights, trade credit is classified as unsecured junior debt and has the lowest priority.[14] The strict priority order, in combination with typically few assets in the bankruptcy estates, implies that recovery rates on claims for unsecured junior creditors are extremely low. For example, Thorburn (2000) documents that the average (median) recovery rate for unsecured junior creditors is around 2 (0) percent in Sweden.

Sweden is not atypical with respect to the priority rights; the junior priority status of trade debt is a common feature across legal systems (see, e.g., Cuñat and Garcia-Appendini, 2012). For example, very similar to the Swedish case, trade creditors in the UK are unsecured junior creditors unless they have included a Retention of Title clause in the sale contract. However, the Retention of Title clause is not commonly used, which implies that recovery rates for trade creditors on average are very low in the UK (Franks and Sussman, 2005). Another example is the US, where trade creditors can reclaim goods that are unprocessed and unsold within ten days of delivery. These are fairly strict conditions for trade creditors' scope to avoid trade credit losses. Accordingly, Bradley and Rubach (2002) report survey evidence showing that non-payments by trade debtors are the prime cause of financial distress and bankruptcy.

In order to measure bankruptcy we adopt the following natural definition of a firm failure. A firm has failed if declared bankrupt in a legal sense, i.e., a liquidation decision by court ruling. This bankruptcy measure thus captures firm events similar to those underlying US Chapter 7 filings for bankruptcy. Bankruptcy events are different from the events explored in Boissay and Gropp (2013), which correspond to late payments on trade credit debts.

Beside the data set on bankruptcy events, we have information on the existence of all individual claims, exceeding SEK 5,000 (approximately USD 700), that were held on bankrupt firms by unsecured junior creditors (trade creditors), over the period 1992–2011. For the sub-period 1996–2011 we also have information on the size of each of these claims. The credit bureau collects this information from reports that the court-appointed trustees provide to the bankruptcy court and to the Swedish Enforcement Authority "Tillsynsmyndigheten för konkurser" (TSM). A majority of these claims is associated with corporate bankruptcies (around 80 percent) and the remainder mainly with bankrupt sole proprietorships. The data always contain information on the date of the trade debtor bankruptcy and the identity of the associated trade creditor(s), i.e., for the years 1992–2011. This information allows us to construct our key variable; an indicator of whether, or not, a firm at time t has experienced a trade debtor failure. For

[14] Swedish law admits contracts of retained ownership with the trade creditor for delivered goods until full payment has been accomplished, provided that goods have not been processed or resold. In practice such contracts are of little consequence. The trade credit claims observed in our data set correspond to unsecured junior claims without any retained ownership rights.

the most recent 5-year period, 2007–2011, the data set also contains the identities of the bankrupt trade debtors, thus an important extension of the conditioning set. We will therefore use the period 2007–2011 as our baseline sample. All models where the debtor identity is superfluous are also estimated on the extended sample periods, 1992–2011 or 1996–2011. By using several sample periods we hope to extract as many insights as possible from our data.

Insurance contracts providing protection against trade debtor failures are not common in Sweden, possibly due to the moral hazard problem that such contracts introduce by altering firms' motives to avoid trade debtor failures. A potential confounder is factoring firms' operations that have become a prosperous industry in Sweden. They allow suppliers to borrow against their accounts receivable as collateral. Alternatively, but much less frequent, factoring firms can purchase the claims on trade debtors. Only if a supplier sells an invoice will the ownership of the claim be transferred to the factoring firm, and make—conditional on the trade debtor's failure—the factoring firm appear as a trade creditor in our data set. However, we note that factoring firms are remarkably infrequent trade creditors, most likely due to the thorough screening process they undertake before purchasing trade credit claims, and thereby avoid high-risk trade debtors. Nevertheless, in the empirical analysis we exclude factoring as well as other financial firms.

The credit bureau has also provided us with data on accounting statements and balance sheet information for all Swedish corporate firms during the period 1989 to 2011. These data have been used in earlier contributions, see Jacobson et al. (2013) for a comprehensive overview. This information is collected by the credit bureau from the Swedish Companies Registration Office (SCRO).[15] In Sweden, as in many other countries, firms have considerable discretion in choosing a fiscal year period for their financial statements. For a large fraction of the firm-year observations in our sample the fiscal year starts in the middle of a calendar year. We deal with this by interpolating the financial statements such that their fiscal year periods correspond to calendar years.[16] Moreover, from the SCRO we obtain data on corporate registration dates, which we use to determine the age of the firms.

We construct an industry classification based on one-digit SNI codes (equivalent to US SIC codes) obtained from the accounting statements. Financial firms and utilities are omitted, since these firms are subject to regulations. We also omit firms where information on industry belonging is missing.[17] Since

[15] Swedish law requires every corporate to submit an annual financial statement to the SCRO, covering balance sheet and income statement data in accordance with EU standards. Moreover, every corporate is also required by Swedish law to hold in equity a minimum of SEK 100,000 (USD 14,000).

[16] See Jacobson, Giordani, von Schedvin, and Villani (2011) for a detailed overview of the applied interpolation procedure. The shares of shorter (less than 12 months) and longer (more than 12 months) statements are both around 5 percent. Whereas shorter than the stipulated 6 months happen, statements covering a longer period than the allowed 18 months are very rare. Over time, the annual shares of shorter/longer statement periods have come down from about 8 percent to currently around 4 percent. Thus, an overwhelming majority of statements concern a period of 12 months. However, out of the 90 percent of the total number of statements, only 48 percentage points coincide with a calendar year, and hence 42 percentage points refer to other 12 month periods. In these calculations we have allowed for a given calendar year to begin in mid-December the previous year, and end in mid-January the following year.

[17] The corpotate firms that we consider belong in one of the following industries: agriculture, manufacturing, construction,

the focus of the paper is on the role of trade credit issued for commercial purposes, we further restrict our sample to firms with real sales and assets exceeding SEK 100,000 (deflating by means of consumer prices, using year 2000 prices as a basis).[18] Furthermore, a small fraction of the financial ratios in our sample is made up of severe outliers. In order to make sure that our results are not distorted by outliers, we have chosen to winsorize the financial ratios according to the 1^{st} and 99^{th} percentile, which is common practise, see, e.g., Shumway (2001).

3.2 Descriptive statistics

3.2.1 Firm characteristics and trade debtor failures

Table 1 reports descriptive statistics for a set of firm-specific variables that characterize the firms in this study. The table is organized for all firm-years; and for firm-years that were, and were not, associated with a trade debtor failure.[19] The first two rows show that the average amounts of accounts receivable- and accounts payable-to-total assets are 15.8 and 10.5 percent, respectively. Hence, Swedish firms issue a substantial amount of short-term financing to their customers, which is in line with reports on usage in other countries showing that trade credit is indeed an important source of short-term financing around the world (see Cuñat and Garcia-Appendini, 2012). The table further shows that firms that experience a trade debtor failure on average issue more trade credit; these firms have an average ratio of accounts receivable-to-assets of 24.9 percent as compared with 15.3 percent for firm-years with no trade debtor failure experience. Thus, this highlights the credit risks that firms face by issuing trade credit.

[Insert Table 1 about here.]

Moreover, according to Table 1, firms that experience a trade debtor failure on average hold less cash and liquid assets, have less fixed assets, are larger, are older, have a better credit rating, and are less dependent on external financing. This is in agreement with findings previously reported in the trade credit literature, showing that larger and older firms with better access to external financing issue more trade credit (see, e.g., Petersen and Rajan 1997; and Giannetti, Burkart, and Ellingsen 2011). Although firms that experience trade debtor failures are on average larger and older, their annual bankruptcy frequency is nevertheless higher, 2.6 as compared with 1.4 percent in the period 2007–2011, and 4.6 as compared with 1.9 percent in the period 1992–2011, which indicates that trade debtor failures potentially are an important risk factor for trade creditors.

By combining bankruptcy frequencies with the number of observations in each sub-group, we can calculate the fraction of creditor failures associated with a trade debtor failure. For the 1992-2011 period,

retail, hotel and restaurants, real estate, transports, and consulting and rental.

[18] SEK 100,000 corresponds to around USD 14,000.

[19] Bankrupt firm-years are assigned to the 'trade debtor failure exposure' category if the bankrupt firm experienced a trade debtor failure in the eleven months preceding, or at any point in time after, their failure events (more on this in Section 3.2.2).

18.1 percent of the bankrupt firm-years are associated with a trade debtor failure. This can be compared with an overall trade debtor failure exposure rate (the fraction of firms that in a year face one, or several, trade debtor failures) of 8.3 percent. The trade debtor failure exposure rate is thus on average around 10 percentage points higher for failing firm-years than for non-failing firm-years. This again highlights that trade debtor failure potentially is an important risk factor for firms.

Figure 1 shows the aggregate bankruptcy frequency for the Swedish corporate sector. There are considerable swings in the bankruptcy frequency overall, but these tend to become dwarfed by the Swedish banking crisis episode in 1992 to 1993. The crisis period displays bankruptcy rates around 4.6 percent, as compared with the average rate of around 1.9 percent for the entire sample period. The figure further shows the yearly trade debtor failure exposure rate, which is higher than the aggregate bankruptcy frequency since each bankrupt firm on average obtained trade credit from more firms than one.[20] The yearly fraction of firms that faced a trade debtor failure is highly correlated with the overall bankruptcy frequency, thus the fraction of firms that faced a trade debtor failure was substantially larger during the crisis period in the 1990's (around 16 percent). However, for the sub-period 1994 to 2004, we see that the trade debtor failure frequency remains elevated and the tight link with the aggregate bankruptcy rate is resumed towards the end of our sample period.

[Insert Figure 1 about here.]

Furthermore, the data set allows us to calculate the total amount of claims held by trade creditors on failed trade debtors. Given that the recovery rate for trade creditors is close to zero (Thorburn 2000), the reported claims are a good approximation of the aggregate credit losses trade debtor failures induce on trade creditors. The average yearly amount of claims over the period 1996–2011 is SEK 2.3 billion, which is sizable. An interesting comparison with Swedish banks' total credit losses on loans of all maturities to non-financial firms can be made for the period 2004–2011. The average yearly bank credit losses amount to around SEK 1.5 billion which roughly correspond to two thirds of the trade credit losses. Hence, firm failures impose larger credit losses on the corporate sector as compared with the banking sector.

As noted above, the bankruptcy frequency is larger for firms that experience a debtor failure. For our baseline period, where the identity of the creditors and debtors are observed, we can characterize the trade credit chains in terms of the number of linkages involved, to provide further intuition for the propagation of bankruptcy. We find that 84.5 percent of bankruptcies belong to single-linked credit chains, where a debtor fails but none of the creditors fails. 13.0 percent of the failures are associated with credit chains of two linkages, where at least one of the creditors of a failed debtor in turn fails. The

[20] For the period 2007–2011 we observe that the average (median) number of trade creditors for a bankrupt trade debtor is around 8 (4).

remaining 2.5 percent of bankruptcies belong to credit chains involving three or more links. Hence, a substantial fraction, 15.5 percent, of bankruptcies belongs to chains involving more than one bankruptcy, suggesting the importance of the propagation mechanism for bankruptcy contagion.

3.2.2 Creditor and debtor failure timing

In the data we observe cases where the bankruptcy date of a trade creditor precedes the bankruptcy date of its trade debtor. Panel A in Figure 2 shows the trade creditor and debtor failure timing for the period 2007–2011 and Panel B shows the associated trade credit claims to (creditor) assets. The figure is constructed using a sample where we select all creditor failures associated with a trade debtor failure in the twelve months prior to the creditor failure, or at any point in time after this event (month 0 corresponds to the creditor failure month). If a trade creditor experienced multiple debtor failures, we retain the failure associated with the largest bankruptcy claim. Panel A shows that—conditional on a trade debtor failure—71 percent of the bankrupt trade creditors experienced the debtor failure in the same month, or in the eleven months prior to their failure. 19 percent experienced the debtor failure in the six months after their failure, and 10 percent experienced the debtor failure more than six months after their failure. The main reason for the reverse timing is that it is common for subsequently failing firms to default on their payments in the (occasionally very long) period running up to the actual bankruptcy event (accordingly, e.g., Asquith, Gretner and Scharfstein (1994) document that firm failures are often preceded by an extended period of financial distress). If the size of the claim is sufficiently large, then the debtor's payment default can push the creditor into cash-flow-based insolvency and immediate bankruptcy, whereas it may take additional time before the debtor enters bankruptcy.[21]

Panel B shows the average size of the bankruptcy claim-to-assets for the creditor bankruptcy events that are associated with a trade debtor failure. The average size of the claim-to-assets varies between 5 and 16 percent, which is substantially higher than the 2.0 percent reported for firms in general (see Table 1). Quite intuitively, this indicates that firms that hold a large claim on a bankrupt trade debtor are more likely to fail as a consequence of the credit loss imposed by the debtor failure. The figure further shows that the claims associated with creditor failures that precede debtor failures are on average very large, between 6 and 10 percent of creditor assets, which is consistent with a scenario in which the debtor's payment default pushes the creditor into immediate failure. Nonetheless, in order to avoid a potential bias due to cases where the creditor failure leads the debtor failure for a long period, we will in the empirical analysis omit trade debtor failures that occurred in the years after that of a creditor failure. For robustness, we scrutinize the construction of our key explanatory variables by reporting results from exercises where

[21] Due to the low recovery rates on claims for unsecured junior creditors, it is not common practice for bankruptcy trustees to enforce payments by filing for bankruptcy for the debtor. Thus, the close-to-zero recovery rate mitigates a concern for a reverse relationship. Also, see Footnote 14 on recent statistics on filings of bankruptcy applications.

we omit debtor failures that succeed creditor failures, as well as include all debtor failures irrespective of time after the associated creditor failure event.

[Insert Figure 2 about here.]

Our two key variables in the empirical analysis are dummy variables indicating whether, or not, a firm (possibly, but not necessarily a trade creditor) fails at time t, TCF, and whether or not a firm experienced a trade debtor failure at time t, TDF. We apply the following adjustments for trade debtor failures that take place around the creditor failure date. If we observe $TCF = 1$ for firm i in year t, then we set $TDF = 1$ if we observe a trade debtor failure in the same year, or in the eleven months prior to the trade creditor bankruptcy, and $TDF = 0$ otherwise. For non-bankrupt trade creditor firm-years, i.e., for $TCF = 0$, we simply set $TDF = 1$ if we observe a trade debtor failure in year t, and $TDF = 0$ otherwise. A trade debtor failure is never assigned to multiple years.

4 Empirical Results

This section presents the empirical analysis. We will first address Hypothesis 1 by exploring the relationship between issuance of trade credit and subsequent credit losses incurred by trade creditors in the event of a debtor failure. We will then proceed to an evaluation of Hypothesis 2. By modeling trade creditor bankruptcy risk conditional on trade debtor failure, we are able to quantify the propagation mechanism. An important step here is to challenge the base-line results by performing a series of robustness checks to rule out that these findings are consistent with alternative explanations—confounding factors—such as common shocks, endogenous matching, and reverse causation. Moreover, we seek to closer examine the separate contributions from credit losses and from demand shrinkage for the propagation mechanism, by exploring a set of cross-sectional determinants related to financial frictions, $R\&D$ intensity, and debtor-specific demand dependence. As a final exercise we examine the aggregate relevance of the propagation mechanism, as suggested by Hypothesis 3

4.1 The credit risk associated with trade credit issuance

The descriptive statistics reported in Table 1, suggest that firms that issue more trade credit are more exposed to trade credit related losses. To explore this relationship further, we quantify the credit losses associated with trade credit issuance by estimating a Tobit model, where we regress the sum of bankruptcy claims held by creditor i at time t, scaled by the creditor's total assets at time $t-1$, $Claims_{i,t}/Assets_{i,t-1}$, on the amount of issued trade credit to total assets by firm i in year $t-1$, $Receivable/Assets_{i,t-1}$, a vector of fixed effects, $\boldsymbol{\lambda}_{i,t}$, and a vector of firm-characteristics, $\mathbf{U}_{i,t}$:

$$(1) \qquad Claims_{i,t}/Assets_{i,t-1} = \gamma_1 Receivable/Assets_{i,t-1} + \mathbf{1}'\boldsymbol{\lambda}_{i,t} + \boldsymbol{\delta}'\mathbf{U}_{i,t-1} + \varepsilon_{i,t}.$$

The vector $\lambda_{i,t}$ comprises a set of time-, industry-, location-, age-, and credit rating-fixed effects to control for the impact of business cycle fluctuations, industry belonging, geographic location, firm age, and firm credit-worthiness, respectively. To account for firm-characteristics that influence creditors' propensity to issue trade credit, we include the following firm-specific determinants as documented by, e.g., Petersen and Rajan (1997) and Gianetti et al. (2011); size, asset tangibility, external financing dependence, and profitability. These variables are related to firms' access to external financing and their internally generated funds, and will thus also measure creditors' propensity and ability to supply trade credit. By including quadratic and cubic terms for the firm-characteristics in $\mathbf{U}_{i,t}$, we also allow for potential nonlinear relationships. Since all bankruptcy claims are strictly positive, we estimate the model using a lower truncation limit equal to zero. The coefficient of interest, $\hat{\gamma}_1$, can thus be interpreted as the yearly trade credit losses associated with a change in the level of outstanding trade credit. Table 2 summarizes results from estimations of Eq. (1).

Columns (I) and (II) report coefficients obtained for the periods 2007–2011 and 1996–2011, respectively. The reported coefficients for accounts receivable are positive and significant for both periods. For the longer period, the magnitude of the coefficient suggest that a \$100 increase in the amount of outstanding trade credit is associated with an average increase in yearly trade credit losses of \$7.7. To add perspective on the economic relevance of trade credit losses, we may calculate the losses' share of total assets for the average firm: 1.2 percent (0.77 times the average amount of issued trade credit, which equals 0.158). A sense of magnitude is given by relating the losses to the average yearly returns of 6.7 percent, indicating that the average firm makes losses corresponding to 17.2 percent of total earnings (0.012 divided by 0.067). These results show that trade credit issuance is associated with economically important credit losses.

[Insert Table 2 about here.]

Next, we will approach Hypothesis 1 from a different angle by estimating a version of the Tobit model in which dummy variables are used to categorize the accounts receivable variable into five regions: 5 to 10, 10 to 15, 15 to 25, 25 to 35, and above 35 percent of creditor total assets. This specification is targeted to capture potential nonlinearities in the relationship between trade credit issuance and trade credit losses. The resulting coefficients in Column (III) suggest a weakly concave relationship, such that we observe larger increases in losses when increasing the amount of issued trade credit from low levels. Our interpretation of this result is that firms issuing more trade credit (as a share of assets), are also better at avoiding losses.

For robustness, we consider two additional model-specifications. The first model is a version of Eq. (1) where creditor assets in the denominator of the dependent variable is replaced by creditor sales. In this model, any bias that may arise from scaling both the dependent and the explanatory variables by assets is eliminated. The coefficient reported in Column (IV) shows that the estimate for this alternative specification is very close to the ones reported for our baseline specifications (see Columns (I) and (II)). The second model is a logistic version of Eq. (1), where the indicator variable $TDF_{i,t}$—taking the value 1 if firm i experienced one (or more) trade debtor failure(s) in year t, and 0 otherwise—is the dependent variable. Column (V) reports a positive estimate of the average marginal effect from accounts receivable in the logistic regression model, estimated for the period 1992–2011, and indicating that the risk of experiencing a trade debtor failure is increasing in the amount issued trade credit. The coefficient is both statistically and economically significant; and suggests that a one-standard-deviation shift in the amount of issued trade credit is associated with a 31.1 percent increase in the risk of experiencing a trade debtor failure, measured at the mean of trade credit issuance.

We find, across all specifications, that the estimated impacts of the control variables indicate that larger and older firms, with more tangible assets, and less dependent on external funding, on average make larger losses (not reported in the table, but available). Thus, firms that appear to have better access to external financing, are more exposed to debtor failures.

In sum, the results presented in Table 2 show that increased trade credit issuance is strongly related to subsequent trade credit losses, and to the risk of experiencing a trade debtor failure; hence, in support of Hypothesis 1. The results further show that when controlling for the amount of issued trade credit, firms with characteristics indicating better access to external financing tend to make larger losses on average. The latter finding points towards a selection of high-quality creditors incurring trade credit losses, rather than the opposite; which reduces the concern that results supporting Hypothesis 2 could be spuriously driven by endogenous matching of low-quality creditors and debtors.

4.2 Creditor failure risk imposed by a debtor failure

We will now shift attention to Hypothesis 2 and model the effect on firm failure risk from a hit by a trade debtor bankruptcy. For this purpose we construct a binary response variable $TCF_{i,t} \in \{0, 1\}$ which captures whether, or not, firm i (possibly, but not necessarily a trade creditor) fails ($TCF_{i,t} = 1$) in year t. We define $p_{i,t}$ as the probability that firm i fails in year t, conditional on survival in year $t-1$. The logistic failure risk model for the binary responses is of the form:

(2)
$$\begin{aligned} TCF_{i,t}|p_{i,t} &\sim Bern(p_{i,t}), i = 1, ..., N \text{ and } t = 1, ..., T, \\ \theta_{i,t} &= \ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \beta X_{i,t} + \mathbf{1}'\boldsymbol{\alpha}_{i,t} + \boldsymbol{\eta}'\mathbf{V}_{i,t-1}, \end{aligned}$$

where the logit, $\theta_{i,t}$, is regressed on an explanatory variable indicating the exposure to trade debtor failures, $X_{i,t}$, a vector of fixed-effects, $\boldsymbol{\alpha}_{i,t}$, and a vector of creditor characteristics, $\mathbf{V}_{i,t}$.

As a starting point, to capture the creditor failure risk associated with a debtor failure, $X_{i,t}$ is set to a binary variable $TDF_{i,t} \in \{0,1\}$ capturing whether, or not, firm i experienced a trade debtor failure ($TDF_{i,t} = 1$) in year t; $X_{i,t} = TDF_{i,t}$. We then proceed and evaluate how creditor failure risk is related to the size of the credit loss by substituting $TDF_{i,t}$ with $Claims/Assets_{i,t}$ measuring the size of the claims that creditor i held on failed debtors in year t scaled by the creditors total assets; $X_{i,t} = Claims/Assets_{i,t}$. We also estimate specifications where the claims-size variable is included both linearly and quadratically, to control for potential nonlinear effects; we substitute $\beta X_{i,t}$ with $\boldsymbol{\beta}'\mathbf{X}_{i,t} = \boldsymbol{\beta}'[Claims/Assets_{i,t}; Claims/Assets^2_{i,t}]'$, which will be our benchmark specification. Thus, $\hat{\beta}$ and $\hat{\boldsymbol{\beta}}$ can be interpreted as capturing the specific creditor risk component associated with a debtor failure, or the credit losses arising in a debtor failure.

In order to account for general sources of failure risk, $\boldsymbol{\alpha}_{i,t}$ includes credit rating-, time-, industry- and location-fixed effects to control for credit worthiness, business cycle fluctuations, cross-industry and cross-location heterogeneity. To control for firm-specific failure risk, $\mathbf{V}_{i,t}$ includes data on firms' capital structure, cash and liquid asset holdings, profitability, size, and age.[22] These are variables that are documented as important determinants of firm failure (see, e.g., Shumway, 2001; Campbell et al., 2008; Jacobson et al., 2013; and Giordani et al., 2014).

4.2.1 Main results

Table 3 shows results for Eq. (2) where the TDF variable is included to control for exposures to trade debtor failures, estimated for the baseline (Panel A) and extended (Panel B) sample periods. Column (I) reports results from a time-, industry- and location-fixed effects logistic regression. For both sample periods, the average marginal effects for the TDF variable are positive and significant, indicating that a trade debtor failure on average is associated with an increased likelihood of a trade creditor failure. Relating the average marginal effects to the bankruptcy frequency in each period shows that a trade creditor is associated with a 53 and a 57 percent increased annual bankruptcy risk, at the mean, for the baseline and extended periods, respectively. Trade debtor failures are thus associated with an economically important rise in trade creditor failure risk.[23]

[Insert Table 3 about here.]

[22] The financial ratios related to capital structure, liquidity, and profitability may capture part of the trade credit channel. That is, debtors may default on their payments in the—sometimes very long—period running up to the failure, which can affect the financial position of the creditors, as documented in the yearly financial statements.

[23] Not reported in the table, we estimate the model on a sample of firms where only medium-sized and large firms are included (firms with at least 50 employees). The obtained average marginal effect for the TDF-variable is positive and significant (statistically, as well as economically). Thus, the results reported in Table 3 are not driven by particular characteristics of small firms.

Column (II) reports results obtained when we apply an OLS estimation of the linear probability model corresponding to Eq. (2). The coefficient for the TDF variable is close to the average marginal effects reported for the logistic models in Column (I).[24] The LPM approach enables conditioning on a triple-interaction variable for the combination of time-, industry-, and location-fixed effects; and thereby provides a comparison of failure risks for creditors, operating within the same industry and the same region, which were, or were not, exposed to debtor failures in a given year. For the industry-fixed effects we use two-digit SNI codes, and location is determined at the county level (Swedish län, 21 regions). Column (III) reports the triple-interaction augmented model results and a comparison with the coefficients reported in Column (II) shows that the impacts of the TDF variable are almost identical. Thus, our main finding persists, when we control for common shocks by including a comprehensive triple-interaction fixed effect in the specification.

Static endogenous matching—trade debtor failures clustering along firm-years of creditors that subsequently fail for other reasons than a debtor failure—is a source for potential bias in the benchmark TDF coefficient. In Column (IV) we report results from estimations of a LPM version of Eq. (2), where creditor-fixed effects are included. In this specification, we can evaluate creditor failure risks for given creditor under time-varying exposures to debtor failures. The results indicate that the impact of the TDF variable is very close to the marginal effects obtained from the logistic model in Column (I), and to the LPM estimate in Column (II). This leads us to conclude that trade debtor failure remains an important risk factor for trade creditors in the light of potentially confounding effects from both common shocks, as well as static endogenous matching.

We will now consider the scope for an impact due to a reverse causal relationship. Upstream and downstream contagion yield predictions in opposite directions, with respect to the role played by the relative creditor-debtor size for the relationship between debtor and creditor failures. On the one hand, under downstream contagion, a debtor failure should be more likely to occur as a result of a distress event with a relatively large and important trade credit provider (from the debtor's perspective). On the other hand, under upstream contagion, a debtor failure involving a substantially smaller debtor than creditor, can be expected to be associated with minor credit- and demand-loss components (from the creditor's perspective), which implies a smaller impact on the creditor's failure risk. Hence, considering a sub-sample of large creditors-to-small debtors, we would enlarge the scope for downstream contagion, and diminish that for upstream contagion. Therefore, recording a weaker failure relationship between creditor and debtor failure for such a sub-sample, can be interpreted as support for upstream rather than downstream contagion, and extenuates concerns about a reverse relationship. Column (IV) evaluates the predictions outlined above, by estimating the average marginal effect of the TDF variable for creditors

[24] The standard errors reported in Table 3 are clustered at the creditor level. Not reported, we verify that the results for the LPM models are very similar when calculating alternative heteroskedasticity-consistent standard errors.

that belong to the top decile of the creditor-to-debtor size distribution, measured by creditor assets over debtor assets, $TDF^{\textit{relatively large creditor}}$, and we find it to be close to zero and statistically insignificant. This result therefore supports the view that the TDF variable captures upstream contagion.[25]

Furthermore, the coefficients for the TDF variable in Columns (I) to (V) capture an average impact measured over all links in the observed trade credit chains. However, it is plausible that the creditor-debtor link position in the credit chain matters for the strength of the propagation mechanism. Our data for the baseline period, 2007–2011, allow us to distinguish between first- and higher-order linkages, related to the concepts introduced by Acemoglu et al. (2012) for studying decaying rates in output volatility in a production economy.[26] We explore this presumption by splitting the TDF variable into two variables: $TDF^{\textit{first-order}}$ and $TDF^{\textit{higher-order}}$, where the first-order variable corresponds to the first link in a failure chain and the higher-order variable corresponds to links further up the failure chain. In other words, $TDF^{\textit{first-order}}$ relates to trade debtor failures where the debtor did not experience a debtor failure prior to his own failure and $TDF^{\textit{higher-order}}$ correspond to debtor failures where the debtor did experience a debtor failure prior to failure. Around 17 percent of all TDF events are classified as $TDF^{\textit{higher-order}}$. The average marginal effects reported in Column (IV) show that the higher-order effect is substantially larger than the first-order effect and the difference is statistically different at the 1-percent level. The average marginal effects suggest that the impact of the higher-order effect is around twice as large. An intuitive explanation for the enhanced impact of higher-order debtor failures is that a larger surprise component is involved. That is, it is much more difficult, if not impossible, for a creditor to evaluate the creditworthiness of debtors of a debtor, and leaves little opportunity to form expectations. The arrival of a $TDF^{\textit{higher-order}}$ can therefore be taken to be largely unexpected.

Trade credit chains may also propagate bankruptcies along the extensive margin. Suppose a debtor failure pushes a creditor into financial distress. While being in distress, the creditor may have to default on payments to its own creditors, which may cause the creditors of the creditor to fail, whereas the initial creditor could become solvent again and be able to avoid bankruptcy. To examine such indirect propagation effects we run a specification where we include a variable to measure indirect TDF shocks, $TDF^{\textit{indirect}}$; based on TDF intensities in firms' customer industries.[27] Column (VII) shows that the

[25] Considering the fraction of the total claims held on a failed debtor, shows that relatively large creditors appear to be more important trade credit providers; trade debtor failure events corresponding to $TDF^{\textit{relatively large creditor}}$ involve creditors holding on average 24 percent of total claims on the failed debtor, as compared with an average of 10 percent of total claims for creditors involved in remaining events.

[26] The main contribution of Acemoglu et al. (2012) is a characterization of how the structure of the intersectoral firm network determines the rate at which aggregate volatility vanishes in a production economy. Slower decays of aggregate volatility in interconnected networks are due to: a first-order contagion effect, where shocks to a (disproportionally well-connected) supplier are transmitted directly to customers in immediately neighboring sectors, and a higher-order contagion effect where shocks to the supplier are transmitted downstream in the production chain. In our framework—a trade credit network—this translates in spirit to upstream first-order, and higher-order effects along the trade credit chain, where the former capture links involving debtors for which the shock originated, and the latter more distant links.

[27] For the construction of $TDF^{\textit{indirect}}$, we follow Acemoglu et al. (2012) and use cross-industry input-output accounts for the construction of a network structure. We use a product-by-product table for 2008, obtained from Statistics Sweden (SCB). The table uses an industry classification at the two-digit SNI level (Swedish equivalent to SIC codes). From the input-output

impact of the $TDF^{\textit{indirect}}$ is positive and statistically significant. This result indicates that trade credit chains play a wider role by transferring economically important indirect effects—in addition to the direct propagation effects.

Having so far established an effect on creditor failure risk from a hit by a debtor failure, it is now both reasonable and intuitive to assume that the magnitude of the effect will vary with the size of the associated credit loss, i.e., the creditor's claims on a failed debtor. Indeed, Figure 3 clearly illustrates a strongly positive relationship between loss size and creditor bankruptcy risk. In the figure we also show model-fits for three univariate models; a logistic model, a logistic model augmented by a quadratic term for the claims, and a linear probability model. Apparently the basic logistic model is doing a poor job in capturing the empirical relationship, whereas the logistic model with a quadratic term and the linear probability model both do substantially better. However, we will adopt all three specifications when exploring the role played by credit losses for creditor risk.

[Insert Figure 3 about here.]

To this end, we re-estimate Eq. (2) and substitute the TDF variable with $Claims/Assets$ as the explanatory variable of interest. Table 4 shows estimation results obtained for the baseline (Panel A) and the extended (Panel B) sample periods. Column (I) reports results from a logistic model. The average marginal effects for the $Claims/Assets$ variable are positive and statistically significant for both periods, indicating that a larger credit loss is associated with an enhanced creditor failure risk.

[Insert Table 4 about here.]

Turning to the logistic model augmented with a quadratic term for the claims-size variable, reported in Column (II), we obtain substantially larger average marginal effects. Their magnitudes double for both the baseline and extended periods, confirming the augmented logistic model specification suggested by Figure 3. The average marginal effects suggest that a one-standard-deviation larger loss imposes an increase in the annual bankruptcy risk of 70 and 59 percent, at the mean, for the baseline and the extended period, respectively. These results clearly indicate that creditor risk is enhanced in the size of trade credit losses. We shall take this specification to be our *benchmark model* in the subsequent exploration of cross-sectional heterogeneity in trade creditor failure risk.

We proceed by estimating a linear probability version of the model, including a triple-interaction fixed effect to control for common shocks. The triple-interaction specification evaluates the failure risks for creditors operating within the same industry and region, in a given year, with respect to different

accounts we know the share of output produced by industry i that is used as input by industry j, and denote it by $w_{i,j}$. The indirect variable is defined as: $TDF_{i,t}^{\textit{indirect}} = \sum_j w_j \times TDF\ frequency_{j,t}$, where $TDF\ frequency_{j,t}$ is the fraction of firms in industry j that experienced one, or more, trade debtor failures in year t.

claims-size exposures to failed debtors. Column (III) shows that the LPM coefficients for the claims-size variables are now substantially stronger, confirming a pronounced role for trade credit losses in determining creditor failure risk.

In Column (IV) we report results from a LPM aimed at dealing with the static endogenous matching problem by including creditor-fixed effects to evaluate the failure risk for given creditor under time-varying exposures to debtor failures. As in the previous case of interacting fixed effects estimation, we find that the coefficients for the claims-size variables are now enhanced as compared with the marginal effects obtained from the benchmark model. Hence, we conclude that our results persist—and if anything, are strengthened—when controlling for endogenous matching.

Finally, Column (V) reports results for a model where we take one step further—beyond the triple-interaction fixed effects—to control for any spurious effects from common shocks, as well as unobserved debtor characteristics. This model includes a debtor-fixed effect specification and is estimated for the baseline period 2007—2011, in which we can observe the identities of both creditors and debtors. The debtor-fixed effect specification evaluates the failure risks of creditors with different trade credit exposures to the same debtor. We find that the claims-size coefficient remains positive and significant. Thus, when common shocks—to a considerable extent—and debtor characteristics are completely accounted for, our conclusion about the effectiveness of debtor failure shocks being reflected in the size of claims is intact.

4.2.2 Additional robustness tests

To further evaluate the validity of our results with respect to model specification and to the three alternative explanations—common shocks, endogenous matching, and reversed causality; we will perform additional robustness tests and present the results in Tables A2 and A3.

The first set of models are intended to examine the robustness of our Hypothesis 2 appraisal when, in turn, allowing for non-linear relationships; the inclusion of additional firm failure determinants; and both a stricter and a looser event window definition for our claims-size variable. Firstly, using a spline version of our debtor-fixed effects model, we can accommodate non-linear relationships between bankruptcy risks and firm controls related to capital structure, cash and liquid asset holdings, profitability, size, and age.[28] The magnitude of the claims-size coefficient in Column (I) is very close to the one reported for the debtor-fixed effects model (Column (V) in Table 4). Secondly, by augmenting the debtor-fixed effects model with the additional control variables working capital ratio and asset turnover ratio, we can benchmark against the classical Altman's (1968) z-score failure-prediction model. The resulting

[28] We apply an additive spline model where we include knots at the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles of each control variable (the model corresponds to a LPM version of Eq. (5) in Giordani et al. (2014)). They show that a small number of knots is sufficient to provide a good approximation of the non-linear relationships between the selected set of control variables and firm failure risk.

claims-size coefficient in Column (II) is similar in size to the one reported for the debtor-fixed effects model in Table 4. Thirdly, by considering on the one hand a stricter criterion, and on the other hand a looser criterion, for eligible debtor failure dates with respect to the associated creditor failure date, we can challenge the construction of the event timing for our results. The claims-size coefficient in Column (III), when using debtor failures occurring no later than one month after the creditor failure, is very close to the Table 4 result. Likewise, running the debtor-fixed effects regression including all debtor failures, irrespective of timing, and assigning them to the creditor failure year, yields a slightly larger coefficient, as presented in Column (IV). These results lead us to conclude that the choice of event window is not critical for the recorded impact of the claims-size variable.

The next model scrutinizes the choice of industry classification level by using 5-digit industry classes instead of 2-digit ones. Column (V) reports results for a 5-digit version of the triple-interaction model (c.f. Column (III) in Table 4); the claims-size coefficient is close in magnitude and significant, which strengthens our earlier conclusion that common shocks are unlikely to influence the effect from credit losses on creditor failure. In order to further control for common shocks we next introduce interacting fixed effects for year$\times$creditor-location, year$\times$creditor-industry, and year$\times$debtor-industry. Hence, the model simultaneously controls for shocks to both creditor and debtor industries. The obtained claims-size coefficient in Column (VI) is positive and significant, suggesting that our results are not influenced by creditor- nor debtor-industry shocks.

Moreover, Columns (VII) to (IX) present results for a set of models that are specified to control for the influence of a dynamic endogenous matching. Firstly, in Column (VII) we show that low-risk creditors exhibit a positive relationship between failure risk and the size of the trade credit loss, suggesting that our benchmark results are not driven by the matching of high-risk creditors and high-risk debtors. In Column (VIII) we report results for a model estimated on the sub-sample of higher-order debtor failures, i.e., debtors that themselves experienced a debtor failure around their failure dates. Since higher-order debtor failures arguably contain a larger element of surprise, we expect that potential selection effects should be down-played for this sub-sample. The resulting coefficient is positive and significant—and of a similar order of magnitude, as the one for the full sample. Our interpretation is that dynamic endogenous matching is less likely to be a concern. By the same token, we estimate a model on a sub-sample of low-risk debtors. The idea is that the failure of a low-risk debtor should be more surprising to its creditors, and that an endogenous matching therefore—if any—plays only a minor role. The obtained claims-size coefficient in Column (IX) is positive and significant, close in size to our previous result, which we again interpret as evidence against endogenous matching.

Finally, Table A3 reports results for a version of our benchmark model estimated on a data set with quarterly observations.[29] The claims-size variable corresponds to trade credit losses in quarter t scaled by creditor assets in quarter $t-4$. We follow an approach proposed in Campbell et al. (2008) and estimate the failure probability j quarters ahead, conditional on survival in quarter $j-1$. This allows us to more carefully explore variation over time in the impact on creditors' failure risk from trade credit losses. The table reports results from models estimating the concurrent failure risk, i.e., creditor failure occurring within the same quarter as the trade credit loss was incurred, ($j=0$), and then the conditional failure risks in quarters 1, 2, 3, 4, 6, and 8 ahead. Column (I) shows results for the model estimating concurrent failure risk. The average marginal effect is positive and significant suggesting that credit losses impose an immediate increase in creditors' failure risk. Furthermore, Columns (I) to (VI) show that trade credit losses have a positive impact on creditor failure risk up to six quarters ahead. These findings suggest that our empirical approach, exploring the impact of trade debtor failure using a one-year window, is— if anything—a conservative one. Nevertheless, we opt for a parsimonious annual setup where the length of the window coincides with the frequency of the yearly financial statements. This fits the purpose of the next sub-section, where we examine cross-sectional heterogeneity in the creditor risk imposed by trade credit losses.

4.3 Relative importance of trade credit losses and demand shrinkage

To this point, our results show that trade creditor and debtor failures are positively related. The documented effect is both statistically and economically significant. The results further show that the relationship is substantially enhanced in the size of the trade credit loss. Our robustness analyses reject that these results are seriously affected by common shocks, endogenous matching, or a reverse relationship. Thus, the findings support the prediction that trade debtor failures impose an increased failure risk on their trade creditors. Nevertheless, it cannot, based on the evidence presented so far, be determined whether the increased risk is due to the credit loss, or to an associated decline in demand. We therefore proceed with an evaluation of the relative importance of credit losses versus declines in demand for the failure propagation mechanism. In particular, we take the benchmark version of Eq. (2) and interact the claims-size variables in $\mathbf{X}_{i,t}$ with various propagation factors $Z_{i,t}$—one at a time—in order to determine cross-sectional variation in the impacts on creditor failure risk:

$$\theta_{i,t} = \boldsymbol{\beta}_1'\mathbf{X}_{i,t} + \boldsymbol{\beta}_2'\mathbf{X}_{i,t}Z_{i,t-1} + \beta_3 Z_{i,t-1} + \mathbf{1}'\boldsymbol{\alpha}_{i,t} + \boldsymbol{\eta}'\mathbf{V}_{i,t-1} \quad (3)$$

We use the obtained estimates to evaluate the average marginal effects of the claims-size variables at the 10^{th} and 90^{th} percentiles of the conditioning variable, $Z_{i,t}$. The strategy is to scrutinize and exploit

[29] As discussed in Section 3, we have out of necessity standardized the annual financial statements for the Swedish corporate firms so that they coincide with calendar years. The standardization can just as well be done with respect to calendar quarters, allowing for the quarterly models underlying Table A3, using all failure events and the same set of control variables.

determinants that should play a role for the impact of trade credit loss, but not for demand loss, and vice versa.

4.3.1 External financing dependence, liquidity dependence, and *R&D* intensity

To evaluate the scope for increased risk caused by the trade credit losses (as opposed to demand shrinkage), we will examine variation in the propagation mechanism with respect to measures of financial constraints. The effect of a credit loss—but much less so, a decline in demand—should depend on whether creditors can offset losses by accessing external financing, or cover for them with liquidity holdings. To this end, we make use of Rajan and Zingales's (1998) measure of external financing dependence, and of Raddatz's (2006) measure of liquidity dependence. On the other tack, we explore whether creditors operating in *R&D* intense industries are more exposed to debtor failures than the opposite. If supplier-customer relationships are stronger and more important in industries characterized by *R&D*, then presumably *R&D* intense creditors are more vulnerable to a debtor failure in the demand-loss dimension. Table 5 reports results from an estimation of Eq. (3) where we interact the claims-size variables with measures of external financing dependence, liquidity dependence, and *R&D* intensity. The table reports conditional marginal effects calculated with respect to the 10^{th} and 90^{th} percentiles of each conditioning variable.

[Insert 5 about here.]

Column (I) in Table 5 reports results for a model where the claims-size variable is interacted with the exogenous variable measuring firms' external financing dependence (*EFD*). For the baseline period, the average marginal effect is lower for creditors operating in industries characterized by a low external financing dependence as compared with a high external financing dependence. The difference in marginal effects between the two groups is not statistically significant. However, for the extended sample period, corresponding marginal effects for the claims-size variable show that the effect is statistically lower (at the 10-percent level) for firms in industries characterized by a low external financing dependence.

In order to sharpen the analysis we will streamline the external finance dependence-measure by constructing a dummy variable indicating whether, or not, the firm belongs to an industry characterized by a positive external financing dependence ($0 < EFD$).[30] Column (II) shows that for both the baseline and the extended sample periods, creditors belonging to industries that are dependent on external financing are substantially more exposed to trade credit losses. The marginal effects for creditors that are dependent as compared with independent are substantially larger for both periods. Differences between the groups are significant at the 1-percent level.

[30] Around 58 percent of the firm-year observations, in both the baseline and in the extended period, involve firms that are characterized as dependent on external financing.

In parallel to the exogenous measure of firms' external financing dependence, we will now consider another exogenous measure aiming at capturing variation in firms' liquidity dependence. Thus, Column (III) shows results with respect to the claims-size variable interacted with firms' liquidity dependence. The marginal effect of the credit loss is around twice as large for liquidity-dependent creditors. The differences in marginal effects pertaining to liquidity dependence are statistically significant at the 1-percent level, for both periods.

We will now shift the perspective and introduce variation in the demand channel and by means of interactions with the claims-size variables study the implications for marginal effects. Column (IV) presents the results for interactions with firm *R&D* intensity, which we believe will capture systematic variation in creditors' vulnerability to demand losses. For both the baseline and the extended sample periods, we observe that the marginal effect of the claims-size variable is substantially stronger for creditors operating in *R&D* intense industries compared with creditors in industries of low *R&D* intensity. These results indicate that demand losses do play a role in explaining portions of the increased creditor risk due to debtor failure. Nevertheless, the estimates also suggest that the credit loss channel remains active in industries in which the demand channel is downplayed according to the $R\&D$ intensity measure.[31,32]

Summing up, the results reported in Table 5, Columns (I)–(IV), suggest that creditors operating in industries characterized by a high external financing dependence, and similarly when operating in liquidity-dependent industries, are more exposed to the size of credit losses. These results are consistent with theories predicting that the propagation mechanism in trade credit chains should be more pronounced for financially constrained firms. Moreover, we find that the risk imposed by a debtor failure is stronger in *R&D* intense industries, implying a role for the demand channel in determining overall effects from debtor failures.

4.3.2 Creditor-specific determinants of the propagation mechanism

It is reasonable to expect considerable heterogeneity in the propagation mechanism with respect to creditor characteristics. Specifically, one would think that characteristics related to borrowing capacity and liquidity position matter: leverage, cash and liquidity holdings, and earnings. Clearly, and contrary to the analyses above—based as they are, on exogenous industry measures of external financing and liquidity dependence—we must now allow for some endogeneity concerns. Nonetheless, in light of the

[31] Firms in highly *R&D* intensive industries tend to have relatively more intangible assets, which are harder to pledge as collateral. This opens up for the possibility that the *R&D* measure is confounded by firms' access to external financing. We deal with this concern by controlling for asset tangibility (results are not reported in the table, but available). Eq. (4) where *Z* corresponds to the *R&D* measure is augmented with a variable corresponding to the creditors' tangibility assets-to-assets and interaction terms between the claims-size variables and tangible assets variable. The obtained marginal effects closely coincide with the ones reported in Column (IV) in Table 5.

[32] We challenge the results reported in Columns (I) to (IV), Table 5, by estimating a LMP version of Eq. (3) saturated with a triple-interaction between time, industry, and location (as in Column (III), Table 4) to account for potential common shocks. The obtained results for this augmented model specification align with the reported ones.

results obtained for the exogenous classifiers, we argue that it is interesting to complement the analysis by directly exploring creditor-specific measures of financing and liquidity constraints. In addition, given the length of the extended sample period, we may also quantify variation in the propagation mechanism over the business cycle. Columns (V) – (VIII) in Table 5 organize results from estimations of Eq. (3) in which we now interact the claims-size variables with measures of the creditors' leverage, cash and liquidity holdings, earnings, and real output growth—one characteristic at a time.

The first creditor-specific factor that we consider is a fundamental one: corporate capital structure. The credit losses due to a trade debtor failure imply that the value of the creditors' assets is reduced. A sufficiently large credit loss may therefore push a creditor into balance-sheet-based insolvency. The risk that a trade debtor failure will push a creditor into insolvency is therefore dependent on the creditor's indebtedness. More leveraged creditors should thus be more vulnerable to the credit losses in a trade debtor failure. Along these lines, Hertzel et al. (2008) propose the hypothesis that highly leveraged firms, due to less financial flexibility, are more exposed to trade debtor failures. That is, highly leveraged firms may be constrained in the amount of additional external financing that they can raise in order to offset the incurred credit loss. Accordingly, Column (V) in Table 5 shows that the marginal effects are significantly stronger for highly leveraged firms, as compared with less leveraged ones.[33] These results suggest that trade creditors with higher leverage levels are indeed more vulnerable to trade debtor failures.

Kiyotaki and Moore (1997) propose that the propagation of corporate failure is mitigated if the trade creditors are cash-rich. More specifically, the credit loss that a trade debtor failure imposes on creditors, implies a shock to the creditors' liquidity-holdings. If the credit loss is large enough, then it may push the creditor into cash-flow-based insolvency. Using corporate cash-holdings, we will take this idea to the data. Column (VI) shows that the claims-size variables only exhibit a positive and significant impact on cash-poor creditors, and no impact on cash-rich creditors. Thus, these results suggest that creditors with a sufficient amount of cash holdings can absorb the credit loss imposed by trade debtor failures, in line with Kiyotaki and Moore's (1997) prediction.

Following a similar intuition as for the role of cash and liquidity holdings, we examine whether ex ante profitable trade creditors facing a trade debtor failure are less likely to fail themselves. Column (VI) shows that creditors with high earnings are less exposed to the credit loss imposed by debtor failures.

Finally, an interesting question is whether trade creditors' vulnerability to trade debtor failure depends on the state of the business cycle? Access to external financing is potentially restricted during economic downturns, c.f. Bernanke and Gertler (1989), which reduces trade creditors' opportunity to offset credit losses by raising external finance. Column (VIII) shows that the marginal effect of the claims-size

[33] We have removed the credit-rating dummy in the regressions where we condition the impact of claims-size on leverage, since credit ratings are highly correlated with creditors' leverage ratios.

variables is enhanced in economic downturns. Of course, although the external financing argument is likely to hold and operate through the credit loss channel, one must also acknowledge demand-driven effects. Recessions involve reductions in aggregate demand, so in this context we should also expect pronounced demand effects from trade debtor failures.

In sum, the results in Columns (V)–(VIII) show that the impact of a trade credit loss is alleviated for firms that are less leveraged, are cash-rich, or are highly profitable; and it is enhanced in economic downturns. Thus, these results suggest that creditors that appear to be more credit and liquidity constrained, are more exposed to trade credit losses. The results therefore offer further support for the notion that trade credit losses are an important factor for the documented propagation mechanism.

4.3.3 Debtor-specific demand dependence

In an attempt to cast more light on the roles played by the credit and demand loss channels for creditor failure outcomes, we will now consider debtor-specific demand. To this end, we construct a proxy aimed at capturing the importance of debtor-specific demand in relation to overall demand for creditors' goods and services. The starting point is to consider the size of the claim that the creditor holds on a failed debtor. As noted earlier, the average time to payment for trade credit contracts in Sweden is one month. If we are willing to assume that the debtor is a repeated customer, buying a similar monthly amount, and that the recorded loss corresponds to all purchases done in a single month, we can then calculate the creditor's yearly sales to that specific debtor as: $12 \times Claims$. It follows that $12 \times Claims/Sales$ will give an approximation for the share of a creditor's total sales that is targeted to the specific debtor, henceforth labeled as debtor-specific demand.

We first explore the idea that although the fraction of a creditor's total sales to a specific debtor may be small—downplaying the demand channel—the debtor failure can nevertheless impose a substantial credit loss in relation to the creditor's assets, $Claims/Assets$, and through the credit loss channel have an effect on creditor failure risk. To this end, we take the benchmark version of Eq. (2) and interact the claims-size variables in $\mathbf{X}_{i,t}$ with a dummy variable reflecting debtor specific-demand, D_i:

$$\theta_{i,t} = \boldsymbol{\beta}_1' \mathbf{X}_{i,t} + \boldsymbol{\beta}_2' \mathbf{X}_{i,t} D_{i,t} + \beta_3 D_{i,t} + \mathbf{1}' \boldsymbol{\alpha}_{i,t} + \boldsymbol{\eta}' \mathbf{V}_{i,t-1}, \tag{4}$$

where the model separately is estimated for D_i defined according to three different cutoffs: debtor-specific demand less than 25, 10, and 5 percent; successively narrowing down the scope for a demand channel. Panel A in Table 6 reports marginal effects for the claims-size variables conditional on a debtor-specific demand below each of the three cutoff levels.

[Insert Table 6 about here.]

The conditional marginal effects for the $Claims/Assets$ variables reported in Columns (II) and (IV) show that the impacts of credit losses remain constant, or even increase, across specifications involving progressively smaller debtor-specific demand. Firm conclusions based on the magnitudes of the estimated marginal effects of the claims-size variables may not be warranted. However, it is reasonable to interpret the results as supportive of a trade credit loss channel that generates increased creditor failure risk independently of demand channel effects; in line with Hypothesis 2.

To further evaluate the relative impacts of trade credit and demand losses we proceed and take the benchmark version of Eq. (2) and include both the claims-size variables in $\mathbf{X}_{i,t}$, and the debtor-specific demand variables in $\mathbf{W}_{i,t}$:

$$\theta_{i,t} = \boldsymbol{\beta}_1'\mathbf{X}_{i,t} + \boldsymbol{\beta}_2'\mathbf{W}_{i,t} + \mathbf{1}'\boldsymbol{\alpha}_{i,t} + \boldsymbol{\eta}'\mathbf{V}_{i,t-1}, \tag{5}$$

where $\mathbf{W}_{i,t} = [12 \times Claims/Sales_{i,t}; (12 \times Claims/Sales_{i,t})^2]'$. The idea is to estimate the impact of credit losses, while controlling for the associated demand losses. Rows (1) and (2) in Panel A, Table 6, show that the marginal effects for the claims-size variables is positive and significant, when controlling for the demand share. The impact of the claims-size variables drops slightly in magnitude as compared with the effect obtained in our benchmark specification (c.f. Column (II) in Table 4). The impact from debtor-specific demand is also positive and statistically significant. These results propose that the increased risks that trade debtor failures impose on trade creditors, can be attributed both to the credit losses and to declines in demand.

Whereas our measure of debtor-specific demand can be taken to be a reasonable approximation, there are, nevertheless, reasons for a concern that the estimated demand loss effects are biased. As creditors observe debtors entering into distress, they may react by contracting their credit supply to distressed customers in order to reduce counterparty risk in their accounts receivable. Alternatively, they may choose to increase credit supply to support an important and struggling customer. The former case implies that the debtor-specific demand variable may underestimate true demand loss; and the latter implies an overestimation.[34] Irrespective of direction, the bias is likely to increase the longer a debtor is in distress prior to the bankruptcy. One way to deal with this concern is to estimate a debtor-fixed effects version of the model underlying the results in Rows (1) and (2). By including debtor-fixed effects we can control for any observed and unobserved debtor-specific circumstance, such as time in distress prior to bankruptcy. Column (X) in Table A2 reports results from a debtor-fixed effects model in which both the claims-size and debtor-specific demand variables are included. The coefficients for both the claims-size and debtor-specific demand variable are positive and significant, and of the same magnitude

[34] Recent work by Garcia-Appendini and Montoriol-Garriga (2014) show that, at the extensive margin, trade creditors contract their trade credit issuance to distressed debtors. However, at the intensive margin, trade creditors that continue their relationship with distressed debtors increase the amount of issued trade credit. Since we only observe cases where the creditors maintain a relationship with failed debtors, Garcia-Appendini and Montoriol-Garriga's results suggest that the debtor-specific demand variable may potentially overstate the demand dependence in our analysis.

as the average marginal effects for the model in Rows (1) and (2), mitigating the concern that the latter results are affected by endogenous shifts in creditors trade credit supply prior to the debtor failure.

To further examine whether the two independent channels are borne out by the data, we will estimate a version of Eq. (5) where the claims-size variables and debtor-specific demand variables are interacted with the exogenous measures of external financing and liquidity dependence—one at a time.[35] The intuition is straight-forward: we expect the impact of credit losses to differ substantially between creditors that belong to industries that are dependent on external financing and liquidity, and creditors belonging to industries that are not. The impact of demand losses should vary much less with respect to creditors financial and liquidity constraints. Rows (3) and (4) show the conditional marginal effects for the claims-size and debtor-specific demand variables, separated into independent and dependent firms. Results for both sample periods show that the differences in impact for the claims-size variable are statistically, as well as economically, significant. The same relationship is not observed for the debtor-specific demand variable; conditional marginal effects are of a similar magnitude, irrespective of whether the firm is dependent, or not, on external financing, and differences are statistically insignificant. Rows (5) and (6) show largely similar results for the liquidity dependence measure. For the baseline period we find that the impact of the claims-size variable is significantly stronger for dependent as compared with independent industries; whereas the difference in impact for the debtor-specific demand variable is not significant. However, for the extended period we observe that both the claims-size and debtor-specific demand variable are significantly stronger for firms that are more liquidity dependent.

Finally, we will exploit variation in fundamental demand to study conditional marginal effects for the two independent channels. The idea is that the impact of the demand loss component should be stronger in industries characterized by tighter supplier-customer relationships; whereas we expect the impact of the credit loss component to be much less affected by the strength of the trading partner relationship. In Rows (7) to (10) we report results from models where the claims-size and debtor-specific demand variable are interacted with our measure of *R&D* intensity. The average marginal effects suggest that the impact of the debtor-specific demand variable is substantially stronger in *R&D* intense industries. For the claims-size variable we do not observe any statistically significant difference between firms operating in industries with a low or high *R&D* intensity.

Summing up, by exploring cross-sectional heterogeneity with respect to financial constraints and supplier-customer dependence, we show that the impact of the credit loss component is substantially stronger for financially constrained firms; whereas the demand loss component is enhanced for firms where supplier-customer ties are stronger. These results propose that the risk that trade debtor failures impose on trade creditors is due to both credit losses and a decline in demand.

[35] $\theta_{i,t} = \boldsymbol{\beta}_1'\mathbf{X}_{i,t} + \boldsymbol{\beta}_2'\mathbf{W}_{i,t} + \boldsymbol{\beta}_3'\mathbf{X}_{i,t}Z_{i,t-1} + \boldsymbol{\beta}_4'\mathbf{W}_{i,t}Z_{i,t-1} + \beta_5 Z_{i,t-1} + \mathbf{1}'\boldsymbol{\alpha}_{i,t} + \boldsymbol{\eta}'\mathbf{V}_{i,t-1}$

4.4 Aggregate relevance of the propagation mechanism

The empirical results so far demonstrate the importance of trade credit chains for the propagation of corporate failures at the firm level. However, as a final empirical exercise we will attempt to evaluate the aggregate relevance of the propagation mechanism; and will ask whether contagion chains are quantitatively important at the macro level, as suggested by Hypothesis 3. Whereas a full account for this question is outside the scope of this paper, we believe a simple experiment based on the micro-econometric models documented in Table 3 above will provide some insights. More specifically, by evaluating a counterfactual Swedish economy without any exposures to trade debtor failures; we attempt to show that the propagation mechanism-component constitutes a significant part of the aggregate bankruptcy frequency.

[Insert Figure 4 about here.]

Figure 4 summarizes our findings on aggregate bankruptcy frequencies. The predicted bankruptcy frequency is calculated as follows. The model reported in Column (I) in Panel B, Table 3, is used to assign a yearly bankruptcy probability to each firm in our sample. We then calculate the sum of the bankruptcy probabilities across all firms in each year, which gives us an estimate of the expected number of bankruptcies at a yearly level. The solid black line reports the expected number of bankruptcies over the total number of firm-year observations, thus corresponding to the model's prediction of the yearly, aggregate bankruptcy frequency. The year-fixed effects included in the model specification will fully account for fluctuations in the aggregate bankruptcy frequency, which implies that the estimated frequencies are identical to the actual bankruptcy frequencies reported Figure 1. Now, we calculate alternative predicted bankruptcy frequencies using the prediction model underlying the results in Table 3, for which the propagation mechanism has been shut down by setting the TDF coefficient to zero.[36] Thus, the difference in estimates is a measure of the trade credit chain component in the aggregate bankruptcy frequency. The bars in Figure 1 show the shares of the overall bankruptcy frequency, contributed to by the TDF variable, i.e., the ratio: ((predicted bankruptcy frequency) / (predicted bankruptcy frequency, when $TDF = 0$)) $- 1$. It is important to note that we interpret the results as showing the relative bankruptcy frequencies for the case when propagation is allowed, relative to the case when it is not allowed to play a role, on a year by year basis; it is taken to be a valid experiment in a static sense, but not necessarily in a dynamic one.

The figure shows that the propagation mechanism provides a significant contribution to the overall bankruptcy rate, especially during the crisis years in the early 1990's. The model suggests that in 1993, in the midst of the Swedish banking crisis, around 13 percent of the overall bankruptcy frequency can

[36] The predicted bankruptcy frequency for year t is given by: $\sum_{i=1}^{N_t}(1+\exp(-\left(\hat{\beta}TDF_{i,t}+\hat{\boldsymbol{\alpha}}_{\mathbf{i,t}}\mathbf{1}+\hat{\boldsymbol{\eta}}'\mathbf{V}_{i,t-1}\right)))^{-1}/N_t$, where N_t is the total number of firms active in year t. The predicted bankruptcy frequency without the propagation mechanism is obtained by setting $\hat{\beta}=0$.

be explained by the propagation mechanism. This fraction then gradually falls towards 5 percent in the middle and in the end of the sample period, when normal economic conditions resumed. Trade credit networks are typically characterized by a high degree of interconnectedness; firms tend to be connected to a large number of suppliers and customers. As noted above, resent research proposes that for sufficiently large, or many, shocks, highly interconnected financial networks may exacerbate contagion of counterparty risk to a greater extent than less connected networks would (Acemoglu et al., 2015). This result can explain our finding of an aggravated impact for the propagation mechanism in the crisis years, as compared with normal times.

Furthermore, Jacobson, Lindé, and Roszbach (2005) show that the bankruptcy frequency in Sweden accounts for a significant amount of the variation in macro aggregates, such as GDP, inflation, and nominal interest rates. Thus, to the extent one is willing to acknowledge a role for the overall bankruptcy frequency for macro level outcomes, disentangling the trade credit driven component of aggregate bankruptcies should be informative towards quantifying the macroeconomic relevance of the propagation mechanism.

Taken together, the exercise outlined above suggests that the propagation mechanism constitutes a significant part of the overall bankruptcy frequency, especially during the crisis period. The finding supports the notion that the propagation mechanism plays a role at the aggregate level, as proposed by Hypothesis 3.

5 Concluding Remarks

Theoretical research proposes that the inter-firm linkages induced by trade credit propagate corporate failures. In this paper, we make use of an extensive Swedish data set where we observe if and when firms, in their capacity as issuers of trade credit, experienced a trade debtor failure. These data provide an opportunity to explore credit losses associated with trade credit issuance and quantify the extent to which such losses cause bankruptcies to propagate in the economy.

The empirical analysis is guided by a conceptual framework where we consider two direct effects linking debtor failure and creditor risks: a credit loss channel, and a demand loss channel. The framework also identifies important potentially confounding factors: common shocks, selection through endogenous matching, and reverse causation, that need to be accounted for.

Our empirical analysis yields four key findings. Firstly, our firm-level results show that trade credit issuance is associated with quantitatively important credit losses. Secondly, we document that trade debtor failures are associated with a substantially enhanced bankruptcy risks for the trade creditors; moreover, these risks are elevated in the size of the trade credit losses. Our results persist in specifications controlling for confounding effects from common shocks, endogenous matching, and reverse causation; suggesting a causal propagation mechanism such that debtor failures lead to creditor failures. Thirdly, we evaluate the relative importance of the credit and demand loss channels in models where we condition the estimated effects of trade credit losses and of debtor-specific demand losses on measures of financial constraints and the strength of supplier-customer ties. Our results suggest that both channels are important for the documented propagation mechanism. Finally, we demonstrate that the propagation mechanism constitutes a significant parts of the aggregate bankruptcy frequency. Thus, supporting the notion that trade credit chains may function as an amplifier of idiosyncratic shocks to the aggregate level.

The results presented here build on trade credit being an important source of short-term financing for Swedish firms in combination with an institutional setting where trade creditors have a junior priority status in bankruptcy proceedings. Such conditions prevail across countries and legal systems (Cuñat and Garcia-Appendini, 2012), which suggests that our results are general in nature and extend beyond the firms explored in this analysis.

Our results are helpful in understanding firm failure clustering, and would seem important to account for in the construction of models supporting risk management in financial institutions, e.g., models underlying decision making concerning capital buffer size. The propagation mechanism may amplify credit losses within a bank loan portfolio, as well as give rise to credit loss correlations between banks. Thus, evaluating overall credit risk in a loan portfolio overlooking failure contagion may underestimate sufficient capital buffer requirements; moreover, erroneous capital buffer decisions discarding failure contagion may be potentially more flawed during economic downturns, for which we show that the propagation mechanism is more pronounced. Also, Allen, Babus, and Carletti (2012) propose that bank asset commonality is a source of systemic risk. Along their lines, our results highlight that the documented propagation mechanism may impose a correlation in loan losses across banks and in this way matters for systemic risk.

A comparison of aggregate credit losses in the corporate sector with aggregate credit losses in the banking sector, suggests that the credit losses incurred by Swedish trade creditors amount to at least 50 percent more than the losses Swedish banks face in their lending to non-financial firms. To the extent that we worry about real effects arising from bank credit losses, we should also—on the grounds of the results documented in this paper—worry about trade credit losses. Given that firms may carry substantial financial assets and liabilities on their balance sheets in the form of accounts payable and receivable, they are in effect performing the task of financial intermediation. However, as such firms are financial intermediaries for whom no bank regulation applies, no capital buffer requirements are in place, nor any supervision is carried out. This begs the question if not efficiency gains could be reaped by enhancing policy efforts in this area?

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TABLE 1

DESCRIPTIVE STATISTICS ON FIRM-SPECIFIC VARIABLES

	All firms					Trade debtor failure exposure		Non trade debtor failure exposure			
Variables	Mean	Median	Std	10^{th} perc.	90^{th} perc.	Mean	Median	Mean		Median	
Panel A: 2007–2011											
$Accounts\ receivable/Assets$	0.158	0.092	0.182	0.000	0.432	0.249	0.223	0.153	*	0.084	*
$Accounts\ payable/Assets$	0.105	0.050	0.138	0.000	0.292	0.151	0.109	0.103	*	0.047	*
$EBIT/Assets$	0.067	0.064	0.238	–0.140	0.314	0.073	0.071	0.067	*	0.063	*
$Liabilities/Assets$	0.495	0.463	0.291	0.142	0.874	0.495	0.479	0.495		0.462	*
$Cash\ holdings/Assets$	0.260	0.165	0.268	0.002	0.691	0.156	0.072	0.266	*	0.173	*
$Fixed\ assets/Assets$	0.315	0.193	0.315	0.003	0.843	0.280	0.174	0.318	*	0.195	*
$Assets$ (in SEK 1,000)	33,807	2,034	994,109	362	20,889	203,020	9,410	23,750	*	1,891	*
$Sales$ (in SEK 1,000)	27,995	2 517	575,190	372	25,563	193,056	16,846	18,185	*	2,309	*
$Sales/Assets$	1.941	1.548	1.736	0.186	4.036	2.275	2.051	1.922	*	1.511	*
$Number\ of\ firm\ employees$	10.522	3.000	122.832	1.000	14.000	56.995	9.000	7.760	*	3.000	*
$Firm\ age$	15.122	12.000	13.969	2.000	33.000	21.093	17.000	14.767	*	12.000	*
$Credit\ rating$	3.651	4.000	1.351	2.000	5.000	3.761	4.000	3.644	*	4.000	*
$R\&D\ Intensity$	0.006	0.001	0.017	0.000	0.014	0.006	0.001	0.006		0.001	*
$External\ financing\ dependence$	0.097	0.135	0.346	–0.252	0.587	0.011	–0.023	0.103	*	0.135	*
$External\ financing\ dependence$ (0/1)	0.620	1.000	0.485	0.000	1.000	0.459	0.000	0.629	*	1.000	*
$Liquidity\ dependence$	0.073	0.074	0.059	0.003	0.147	0.080	0.083	0.072	*	0.074	*
$Bankruptcy$ (1/0)	0.015	0.000	0.120	0.000	0.000	0.026	0.000	0.014	*	0.000	*
$Claims/Assets$	0.001	0.000	0.013	0.000	0.000	0.020	0.004				
$Claims/Receivable$	0.024	0.000	0.347	0.000	0.000	0.422	0.021				
Number of firms			272,003			37,050		269,721			
Number of obs.			1,057,935			59,348		998,587			
Panel B: 1992–2011											
$Bankruptcy$ (1/0)	0.021	0.000	0.143	0.000	0.000	0.046	0.000	0.019	*	0.000	*
$Bankruptcy\ claims/Assets^{\dagger}$	0.001	0.000	0.014	0.000	0.000	0.022	0.004				
$Bankruptcy\ claims/Receivable^{\dagger}$	0.024	0.00	0.346	0.000	0.000	0.415	0.023				
Number of firms			445,595			113,523		438,531			
Number of obs.			3,824,572			317,640		3,506,932			

The table reports descriptive statistics for a set of firm-specific variables for the periods 2007–2011 (Panel A), and 1992–2011 (Panel B), grouped on all firm-years when the firm experienced one, or several, trade debtor failures in year t (Trade debtor failure exposure), and firm-years when the firm did not experience a trade debtor failures in year t (Non trade debtor failure exposure). All firm-specific variables correspond to year t – 1. Variable definitions are provided in Table A1. The star (*) reported next to the mean and median values for the 'Non trade debtor failure' group denote that these statistics are significantly different from the 'Trade debtor failure' group's means and medians at the 1 percent level. Differences in means are assessed using a Student's t-test and differences in medians are assessed using the Wilcoxon-Mann-Whitney test.

TABLE 2

CREDIT LOSSES ASSOCIATED WITH TRADE CREDIT ISSUANCE

	Dependent Variables:				
	$Claims/Assets$			$Claims/Sales$	TDF (0/1)
	(I)	(II)	(III)	(IV)	(V)
Variables	Coef.	Coef.	Coef.	Coef.	*dθ/dx*
$Receivable/Assets$	0.071***	0.077***		0.060***	0.142***
	(57.1)	(113.4)		(102.8)	(117.8)
$Receivable/Assets$; 5-10 *p.*			0.020***		
			(52.9)		
$Receivable/Assets$; 10-15 *p.*			0.030***		
			(75.2)		
$Receivable/Assets$; 15-25 *p.*			0.038***		
			(101.6)		
$Receivable/Assets$; 25-35 *p.*			0.044***		
			(107.1)		
$Receivable/Assets$; 35 *p.* -			0.049***		
			(116.1)		
Firm Controls	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Model	Tobit	Tobit	Tobit	Tobit	Logistic
Sample period	2007–2011	1996–2011	1996–2011	1996–2011	1992–2011
Pseudo-R^2	0.367	0.401	0.418	0.448	0.188
F/χ^2	59***	221***	218***	169***	121,981***
Area under *ROC* curve	–	–	–	–	0.806
Number of obs.	1,057,935	3,141,711	3,141,711	3,141,711	3,824,572

The table reports coefficients from Tobit regressions (Eq. (1)) estimating the credit losses associated with trade credit issuance and average marginal effects from a logistic regression estimating the likelihood that a firm experiences one or more trade debtor bankruptcies in year *t*, for the periods 2007–2011, 1996–2011, and 1992–2011. The dependent variable in the Tobit regressions is the size of the claim that the trade creditor has on a bankrupt trade debtor at time *t*, scaled by total (creditor) assets at time *t* – 1, or by total (creditor) sales at time *t* – 1; and the dependent variable in the logistic regression, TDF, indicates whether or not a firm experienced one, or more, trade debtor bankruptcies in year *t*. For the Tobit estimation, we apply a lower truncation limit equal to zero. If a trade creditor experiences multiple debtor failures in a year then we enter the sum of the claims into the dependent variable. Firm controls include the natural logarithm of total assets, tangible assets over assets, external financing dependence, and *EBIT* over assets. Quadratic and cubic terms of the firm controls are included. The firm-specific variables are described in Table A1. Industry-fixed effects correspond to one-digit SNI codes, location is determined at the county level (Swedish län, 21 regions), and credit rating is the rating assigned by the credit bureau UC. The pseudo-R^2 values are calculated according to McFadden (1973). The F-test evaluates whether the parameters associated with the trade debtor failure and the firm-specific controls are jointly equal to zero. The χ^2-statistic refers to a Wald test of the null that all parameters, except the intercept, are jointly equal to zero. The *ROC*-measure refers to the receiving operating characteristic; gauging in-sample, overall predictive ability. *t*-values, calculated using robust standard errors, clustered at the firm-level, are reported within parenthesis. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

TABLE 3

CREDITOR FAILURE RISK ASSOCIATED WITH DEBTOR FAILURES

	Dependent variable: TCF (0/1)						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variables	*dθ/dx*	Coef.	Coef.	Coef.	*dθ/dx*	*dθ/dx*	*dθ/dx*
Panel A. Baseline period							
TDF (0/1)	0.008***	0.011***	0.010***	0.010***	0.008***		0.009***
	(18.9)	(16.5)	(16.0)	(12.4)	(19.1)		(18.1)
$TDF^{\textit{relatively large creditor}}$ (0/1)					−0.001		
					(−0.2)		
$TDF^{\textit{first-order}}$ (0/1)						0.007***	
						(14.3)	
$TDF^{\textit{higher-order}}$ (0/1)						0.015***	
						(16.5)	
$TDF^{\textit{indirect}}$ (0/1)							0.057***
							(4.5)
Pseudo-R^2/R^2	0.227	0.061	0.104	0.591	0.227	0.227	0.235
F/χ^2	28,205***	774***	751***	318***	28,224***	28,221***	23,777***
Area under *ROC* curve	0.881	–	–	–	0.881	0.881	0.885
Number of obs.	1,057,935	1,057,935	1,057,935	1,057,935	1,057,935	1,057,935	825,469
Panel B. Extended period							
TDF (0/1)	0.012***	0.018***	0.018***	0.013***			
	(55.1)	(47.4)	(47.7)	(36.6)			
Pseudo-R^2/R^2	0.177	0.045	0.081	0.467			
F/χ^2	104,047***	4,093***	3,830***	3,615***			
Area under *ROC* curve	0.844	–	–	–			
Number of obs.	3,824,572	3,824,572	3,824,572	3,824,572			
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes	Yes	Yes	Yes
Industry FE	Yes	Yes		Yes	Yes	Yes	Yes
Location FE	Yes	Yes		Yes	Yes	Yes	Yes
Year*Industry*Location FE			Yes				
Creditor FE				Yes			
Model	Logistic	LPM	LPM	LPM	Logistic	Logistic	Logistic

The table reports results from regressions estimating the likelihood that a firm fails as an outcome of facing a trade debtor bankruptcy (Eq. (2) where the *TDF* variable is included to measure the exposure of trade debtor failures). Average marginal effects are reported for the logistic models. Panels A and B report results obtained for the baseline period 2007–2011, and the extended period 1992–2011. The dependent variable, *TCF*, indicates whether a firm is bankrupt or not in year *t*. *TDF* is an indicator variable taking the value one if a firm experienced a trade debtor bankruptcy, and zero otherwise, in year *t*. $TDF^{\textit{relatively large creditor}}$ corresponds to debtor failures for which the creditor belongs to the top decile in the relative creditor-debtor size distribution, measured by creditor assets over debtor assets. $TDF^{\textit{first-order}}$ relates to trade debtor failures where the debtor did not experience a debtor failure prior to his failure. $TDF^{\textit{higher-order}}$ corresponds to debtor failures where the debtor in turn also experienced a debtor failure prior to failure. $TDF^{\textit{indirect}}$ corresponds to the fractions of firms in the creditor's debtor industries that experienced a trade debtor failure. All firm-specific variables correspond to year *t* – 1. The firm-specific variables are described in Table A1. Credit rating-fixed effects are estimated using ratings assigned by the credit bureau UC. Industry-fixed effects are based on one-digit SNI codes, and location is determined at the county level (Swedish län, 21 regions). Industry-fixed effects in Column (II) are based on two-digit SNI codes. The pseudo-R^2 values are calculated according to McFadden (1973). The F-test evaluates whether the parameters associated with the TDF variables and the firm-specific controls are jointly equal to zero. The χ^2-statistic refers to a Wald test of the null that all parameters, except the intercept, are jointly equal to zero. The *ROC*-measure refers to the receiving operating characteristic; gauging in-sample, overall predictive ability. *t*-values are calculated using robust standard errors, clustered at the creditor-level, and are reported within parenthesis. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

TABLE 4

CREDITOR FAILURE RISK ASSOCIATED WITH TRADE CREDIT LOSSES

	Dependent variable: TCF (0/1)				
	(I)	(II)	(III)	(IV)	(V)
		Benchmark			
Variables	*dθ/dx*	*dθ/dx*	Coef.	Coef.	Coef.
Panel A. Baseline period					
$Claims/Assets$	0.100***	0.200***	0.483***	0.367***	0.242***
	(28.6)	(17.5)	(18.3)	(12.7)	(7.0)
Pseudo-R^2/R^2	0.230	0.231	0.106	0.592	0.595
F/χ^2	31,608***	31,878***	766***	320***	16***
Area under *ROC* curve	0.882	0.883	–	–	–
Number of obs.	1,057,935	1,057,935	1,057,935	1,057,935	40,269
Panel B. Extended period					
$Claims/Assets$	0.120***	0.229***	0.547***	0.430***	
	(59.3)	(35.9)	(39.0)	(30.3)	
Pseudo-R^2/R^2	0.204	0.204	0.080	0.433	
F/χ^2	91,859***	92,966***	2,534***	2,599***	
Area under *ROC* curve	0.863	0.864	–	–	
Number of obs.	3,141,711	3,141,711	3,141,711	3,141,711	
Firm Controls	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes	Yes
Industry FE	Yes	Yes		Yes	Yes
Location Fixed effects	Yes	Yes		Yes	Yes
Year*Industry*Location FE			Yes		
Creditor FE				Yes	
Debtor FE					Yes
$Claims/Assets^2$ Included		Yes			
Model	Logistic	Logistic	LPM	LPM	LPM

The table reports results from regressions estimating the creditor bankruptcy risk associated with trade credit losses (Eq. (2) where the *Claims/Assets* variable is included to measure the exposure of trade debtor failures). Average marginal effects are reported for the logistic models. Panel A reports results obtained for the baseline period 2007–2011, and Panel B reports results obtained from the extended period 1992–2011. The dependent variable, *TCF*, indicates whether a firm is bankrupt or not in year *t*. *Claims/Assets* is the sum of the claims that the trade creditor has on bankrupt trade debtors at time *t* to total (creditor) assets at time *t* – 1. Firm controls are: liabilities to assets, cash and liquid assets to assets, *EBIT* to assets, logarithm of total assets, and logarithm of one plus the firm age (both linearly and squared). All firm-specific variables correspond to year *t* – 1. The firm-specific variables are described in Table A1. Credit rating-fixed effects are estimated using ratings assigned by the Swedish credit bureau UC. Industry-fixed effects are based on one-digit SNI codes, and location is determined at the county level (Swedish län, 21 regions). Industry-fixed effects in Column (III) are based on two-digit SNI codes. The pseudo-R^2 values are calculated according to McFadden (1973).The F-test evaluates whether the parameters associated with the trade debtor failure and the firm-specific controls are jointly equal to zero. The χ^2-statistic refers to a Wald test of the null that all parameters, except the intercept, are jointly equal to zero. The *ROC*-measure refers to the receiving operating characteristic; gauging in-sample, overall predictive ability. *t*-values are calculated using robust standard errors, clustered at the creditor-level (except for the model with debtor-fixed effects where clustering is done at the debtor-level), and are reported within parenthesis. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

TABLE 5

CROSS-SECTIONAL DETERMINANTS OF CREDITOR FAILURE RISK ASSOCIATED WITH TRADE CREDIT LOSSES

	Conditional marginal effects of Claims/Assets							
	(I) *External financing dependence*	(II) *External financing dependence* (0/1)	(III) *Liquidity dependence*	(IV) *R&D Intensity*	(V) *Liabilities/ Assets*	(VI) *Cash holdings/ Assets*	(VII) *Earnings/ Assets*	(VIII) ΔGDP
Panel A. Baseline period								
10^{th} perc. (dummy = 0)	0.180***	0.160***	0.130***	0.192***	0.161***	0.300***	0.217***	–
	(9.5)	(10.9)	(6.6)	(15.7)	(13.2)	(16.1)	(16.9)	
90^{th} perc. (dummy = 1)	0.221***	0.251***	0.295***	0.270***	0.292***	–0.059	0.159***	–
	(11.6)	(14.0)	(12.4)	(7.6)	(17.9)	(–1.6)	(14.5)	
p-value	0.177	0.000	0.000	0.037	0.000	0.000	0.000	–
Panel B. Extended period								
10^{th} perc. (dummy = 0)	0.216***	0.198***	0.178***	0.218***	0.169***	0.328***	0.259***	0.280***
	(22.1)	(24.1)	(17.3)	(32.7)	(25.5)	(31.9)	(34.4)	(23.1)
90^{th} perc. (dummy = 1)	0.241***	0.264***	0.300***	0.316***	0.331***	–0.020	0.164***	0.211***
	(23.3)	(27.3)	(21.9)	(16.7)	(35.6)	(–1.1)	(25.5)	(26.0)
p-value	0.096	0.0000	0.000	0.000	0.000	0.000	0.000	0.000

The table reports conditional average marginal effects. Panel A reports results obtained for the baseline period 2007–2011, and Panel B reports results obtained from the extended period 1996–2011. The conditional average marginal effects are obtained from Eq. (3) where each factor, one at the time, is included both linearly and through interactions with *Claims/Assets* and *Claims/Assets*^{2}. The *p*-value refers to a test of the null hypothesis that the marginal effect at the10^{th} percentile is equal to that at the 90^{th} percentile. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

TABLE 6

CONTROLING FOR DEBTIOR-SPECIFIC DEMAND

Panel A		Baseline period			Extended period		
		(I) Mean of $12 \times Claims/Sales$	(II) Conditional marginal effects of $Claims/Assets$		(III) Mean of $12 \times Claims/Sales$	(IV) Conditional marginal effects of $Claims/Assets$	
Row	Threshold (S)						
(1)	≤ 100 percent	0.183	0.200***	(17.5)	0.178	0.229***	(35.9)
(2)	< 25 percent	0.040	0.288***	(6.1)	0.040	0.228***	(11.5)
(3)	< 10 percent	0.023	0.295***	(6.0)	0.023	0.266***	(6.8)
(4)	< 5 percent	0.015	0.361***	(3.6)	0.014	0.208***	(2.8)

Panel B		Baseline period							Extended period						
				10^{th} percentile		90^{th} percentile					10^{th} percentile		90^{th} percentile		
Row	Variables	*dθ/dx*		(dummy = 0)		(dummy = 1)		*p*-value	*dθ/dx*		(dummy = 0)		(dummy = 1)		*p*-value
	A. Overall effects														
(1)	$Claims/Assets$	0.129***	(7.9)						0.155***	(15.9)					
(2)	$12 \times Claims/Sales$	0.011***	(5.9)						0.011***	(9.8)					
	B. $External\ financing\ dependence$ (0/1)														
(3)	$Claims/Assets$			0.089***	(4.2)	0.179***	(6.7)	0.007			0.130***	(10.5)	0.185***	(12.0)	0.005
(4)	$12 \times Claims/Sales$			0.013***	(4.7)	0.009***	(3.3)	0.238			0.011***	(7.2)	0.011***	(6.9)	0.758
	C. $Liquidity\ dependence$														
(5)	$Claims/Assets$			0.084***	(3.0)	0.192***	(6.1)	0.029			0.133***	(8.5)	0.187***	(9.5)	0.066
(6)	$12 \times Claims/Sales$			0.009***	(2.9)	0.013***	(4.1)	0.463			0.008***	(4.3)	0.015***	(7.3)	0.033
	D. $R\&D\ Intensity$														
(7)	$Claims/Assets$			0.128***	(7.3)	0.133***	(2.8)	0.918			0.149***	(14.6)	0.195***	(6.5)	0.139
(8)	$12 \times Claims/Sales$			0.010***	(5.0)	0.018***	(3.6)	0.136			0.010***	(8.8)	0.018***	(5.1)	0.045
	E. $R\&D\ Intensity$ (0/1)														
(9)	$Claims/Assets$			0.129***	(7.3)	0.123***	(2.5)	0.903			0.157***	(15.1)	0.117***	(4.1)	0.187
(10)	$12 \times Claims/Sales$			0.009***	(4.6)	0.022***	(4.3)	0.022			0.010***	(8.0)	0.021***	(6.4)	0.001

Panel A: Columns (I) and (III) report the means of debtor-specific demand, 12**Claims/Sales*, which is less or equal to 100, and less than 25, 10, and 5 percent of creditor's total sales, Rows (1)–(4), respectively. Columns (II) and (IV) reports conditional marginal effects obtained from Eq. (4) for which a variable *D*(12**Claims/Sales* $<$ *S* %) enters linearly and through an interaction term with *Claims/Assets* and *Claims/Assets*^{2}. *D*(12**Claims/Sales* $<$ *S* %) is a dummy variable taking the value one if 12**Claims/Sales* is below the cut-off of *S* percent of creditor's total sales, and zero otherwise. The marginal effects correspond to claims for which *D*(12**Claims/Sales* $<$ *S* %) = 1. Panel B: Rows (1) and (2) report average marginal effects obtained from estimations of Eq (5). Rows (3) to (10) report results from augmented versions of the model reported in Rows (1) and (2), where the variables corresponding to *Claims/Assets* and 12**Claims/Sales* are, in turn, interacted with our measures of financing dependence, liquidity dependence, and *R&D* intensity. A linear term of the propagation factors is included as well. Variable definitions are provided in Table A1. The *p*-value refers to a test of the null hypothesis that the marginal effect at the 10^{th} percentile is equal to that at the 90^{th} percentile. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

FIGURE 1

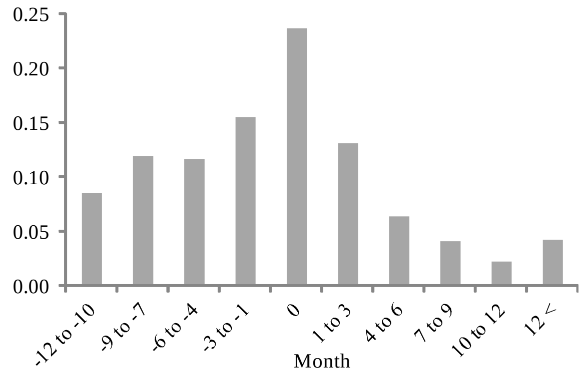
BANKRUPTCY AND TRADE DEBTOR FAILURE FREQUENCIES

The solid line marks the yearly frequency of Swedish corporate bankruptcies (left-hand scale), and the dashed line marks the fraction of corporate firms in Sweden that experienced one, or several, trade debtor bankruptcy(ies) in each year (right-hand scale).

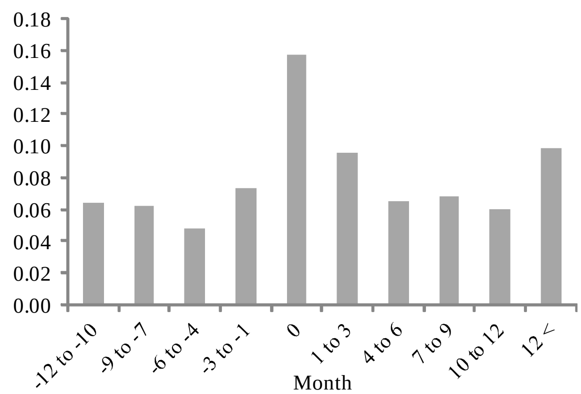
FIGURE 2

TRADE CREDITOR AND DEBTOR FAILURE TIMING

Panel A. Frequency



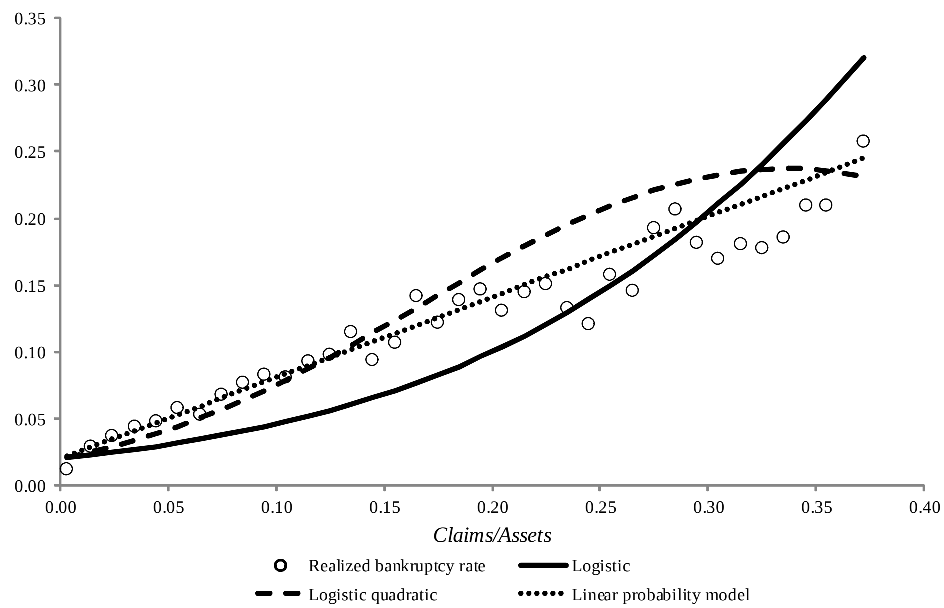
Panel B. $Claims/Assets$



The figure in Panel A provides an illustration of how the timing of trade creditor and debtor failures is played out for the baseline sample period 2007–2011. We have included all creditor failures associated with a trade debtor failure in the 11 months prior to the creditor failure, and all creditor failures associated with a trade debtor failure at any point in time after the creditor failure (month 0 corresponds to the creditor failure month). If a trade creditor experienced multiple debtor failures, then the debtor failure associated with the largest bankruptcy claim is retained. The figure in Panel B shows the means of the associated trade credit claims over creditor assets.

FIGURE 3

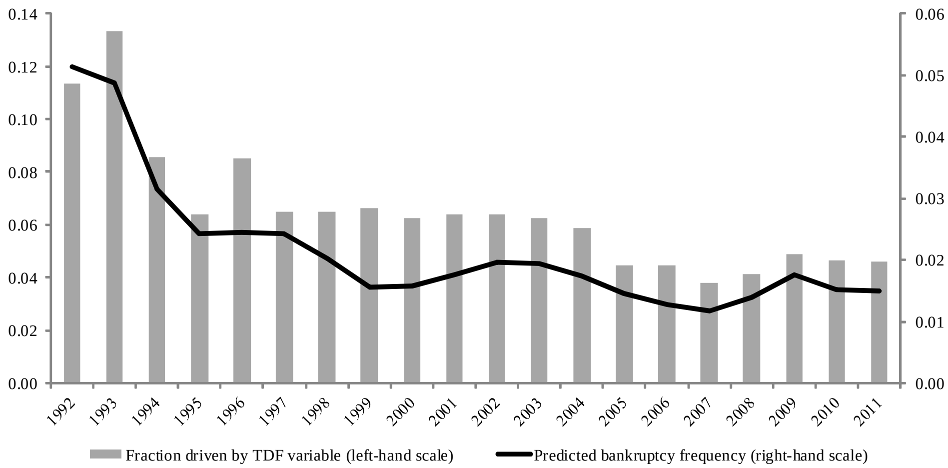
RELATIONSHIP BETWEEN TRADE CREDIT LOSSES AND BANKRUPTCY RISK



The figure provides an illustration of the relationship between the size of bankruptcy claims (*Claims/Assets*) and bankruptcy frequencies (circles), for the period 1996–2011. The bankruptcy frequencies are obtained by first dividing the observations into groups with respect to the size of associated bankruptcy claims: 0–0.01, 0.01–0.02,. . . , 0.37 $<$. In each group, we then calculate the mean of *Claims/Assets* and the creditor bankruptcy frequency, which give pairwise observations displayed as circles in the figure. Moreover, model-fits for three univariate models are included for comparison with the empirical relationship: a logistic model (solid line), a logistic model augmented by a quadratic term for the claims (dashed line), and a linear probability model (dotted line).

FIGURE 4

AGGREGATE RELEVANCE



The figure is constructed based on estimates for the extended period model in Column (I), Table 3. The bars show the percentage contribution of the *TDF* variable to the over-all bankruptcy frequency in each year (left-hand scale) and the solid line illustrates the predicted bankruptcy frequency (right-hand scale).

Appendix

TABLE A1

VARIABLE NAMES AND DEFINITIONS

Variable names	Definitions
TCF (0/1)	Takes the value one if a trade creditor fails in year t, and zero otherwise
TDF(0/1)	Takes the value one if a trade creditor experiences one or more trade debtor failures in year t, and zero otherwise. If $TCF = 1$ then TDF takes the value one if the creditor experiences a debtor failure in the same year or in the twelve month prior to the creditor failure
$TDF^{\text{relative large creditor}}$ (0/1)	Corresponds to debtor failures for which the creditor belongs to the top decile of the relative creditor-debtor size distribution, measured by total assets.
$TDF^{\text{first-order}}$(0/1)	Relates to trade debtor failures where the debtor did not experience a debtor failure prior to his failure
$TDF^{\text{higher-order}}$ (0/1)	Corresponds to debtors failures where the debtor itself experienced a debtor failure prior to its failure
TDF^{indirect} (0/1)	Corresponds to the fraction of firms in the creditor's debtor industries that experience a trade debtor failure (see definition in Section 4.2)
$Claims$	The sum of the claims held on failed trade debtors in year t. The sum of the claims are calculated for all events underlying the TDF variable
$Accounts\ recievable$	The amount of issued trade credit
$Accounts\ payable$	The amount of received trade credit
$EBIT$	Earnings before interest and taxes
$Total\ Liabilities$	Total liabilities excluding accounts payable
$Cash\ holdings$	Cash and liquid assets
$Tangible\ assets$	Property, plants and equipment
$Assets$	Total assets
$Sales$	Total sales
$Sales/Assets$	Total sales over total assets; asset turnover ratio
$Number\ of\ firm\ employees$	Owner manager plus the number of employees
$Firm\ age$	Number of years since first registered as a corporate
$Credit\ rating$	Spans between 1 (high risk) and 5 (low risk) and is the rating assigned by the Swedish credit bureau, UC
$External\ financing\ dependence$	Is calculated according to Rajan and Zingales (1998) for US public firms and assigned to the firms in the sample
$External\ financing\ dependence$ (0/1)	Takes the value one for firms belonging to an industry characterized by a positive external financing dependence, and zero otherwise
$Liquidity\ dependence$	Is calculated according to Raddatz (2006) for US public firms and assigned to the firms in the sample
$R\&D\ Intensity$	The total amount of $R\&D$ expenditures scaled by the total amount of net sales for firms with more than 10 employees, calculated on a two-digit industry level
$R\&D\ Intensity$ (0/1)	Takes the value one for firms belonging to the top 25 percent of industries with the highest $R\&D$ intensity, and zero otherwise

This table provides definitions for the variables used in the analysis.

TABLE A2

ROBUSTNESS

	Dependent variable: TCF (0/1)									
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
$Claims/Assets$	0.259***	0.238***	0.231***	0.313***	0.402***	0.299***	0.175***	0.309***	0.314***	0.179***
	(7.0)	(6.9)	(7.0)	(7.9)	(16.1)	(8.8)	(5.0)	(3.1)	(4.9)	(4.1)
$12 \times Claims/Sales$										0.008*
										(2.0)
R^2	0.597	0.596	0.631	0.471	0.264	0.322	0.604	0.506	0.652	0.595
F-test	4.9***	19.4***	13.6***	23.8***	34.8***	26.8***	9.5***	6.1***	5.6***	14.1***
Number of obs.	40,269	40,269	40,120	40,385	1,057,935	32,743	34,497	5,397	10,540	40,269
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Z-Score Variables		Yes								
Year FE	Yes	Yes	Yes			Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes				Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes				Yes	Yes	Yes	Yes
Year×Ind. FE						Yes				
Year×Loc. FE						Yes				
Year×Ind.×Loc. FE					Yes					
Year×Debtor Ind.FE						Yes				
Debtor FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes
SNI Level. Ind. Classification	1-digit	1-digit	1-digit	1-digit	5-digit	2-digit	1-digit	1-digit	1-digit	1-digit
Mechanism Window	Annual	Annual	Monthly	All	Annual	Annual	Annual	Annual	Annual	Annual
Sample	All	All	All	All	All	All	Low-risk creditors	Higher-order	Low-risk debtors	All
Model	Spline	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM

The table reports results from regressions estimating the creditor bankruptcy risk associated with trade credit losses (Eq. (2) where the *Claims/Assets* variable is included to measure the exposure of trade debtor failures) for the period 2007–2011. Column (I) reports results from a spline version of the debtor-fixed effects model reported in Column (V), Table 5. In the additive spline model we include knots at the 20th, 40th, 60th, and 80th percentiles of each control variable (the model corresponds to a LPM version of Eq. (5) in Giordani et al. (2013)). Column (II) reports results for a debtor-fixed effects model including additional control variables related to the asset turnover ratio and net working capital. Column (III) reports results from a model in which debtor failures that occur after the associated creditor failure are omitted. Column (IV) reports results from a model in which debtor failures that are observed at any point in time after the associated creditor failure are assigned to the creditor failure year. Column (V) reports results from a version of the model in Column (III), Table 5, where the industry is classified at the five-digit level. Column (VI) reports results from a model that includes fixed effects for: year*creditor industry, year*location, and year*debtor industry, where industry is classified at the two-digit level. Column (VII) reports results from a debtor-fixed effect model estimated on a sub-sample of creditors with a credit rating of 3, or better, (corresponding to a yearly default risk of 3.04 percent and below). Column (VIII) reports results from a debtor-fixed effect model estimated on a sub-sample of higher-order debtor failures (debtors that experienced a debtor failure prior to their own failure). Column (IX) reports results from a debtor-fixed effect model estimated on the sub-sample of debtors with a credit rating of 3, or better, just prior to failure. Column (X) reports results from a debtor-fixed effects model including a variable related to the debtor-specific demand, *12*Claims/Sales*. All firm-specific variables correspond to year $t-1$. The firm-specific variables are described in Table A1. The F-test evaluates whether the parameters associated with the trade debtor failure and the firm-specific controls are jointly equal to zero. *t*-values calculated on robust standard errors, clustered at the debtor-level (except for the models in Columns (V) and (VI) where clustering is done at the creditor-level), are reported within parenthesis. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

TABLE A3

FORECASTING MODELS ESTIMATED ON A QUARTERLY FREQUENCY

	$p(TCF_{t+j} = 1 \mid TCF_{t+j-1} = 0)$						
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	$j = 0$	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 6$	$j = 8$
Variable	$d\theta/dx$	$d\theta/dx$	$d\theta/dx$	$d\theta/dx$	$d\theta/dx$	$d\theta/dx$	$d\theta/dx$
$Claims/Assets_t$	0.030***	0.035***	0.032***	0.023***	0.024***	0.032***	0.006
	(8.7)	(8.6)	(6.0)	(3.4)	(3.0)	(3.8)	(0.6)
Pseudo-R^2	0.159	0.158	0.151	0.146	0.137	0.128	0.119
χ^2	14,703***	19,193***	21,458***	20,512***	18,718***	16,777***	13,323***
Area under *ROC* curve	0.884	0.877	0.866	0.857	0.847	0.836	0.825
Number of obs.	3,954,646	3,832,910	3,676,472	3,462,862	3,249,373	2,811,993	2,381,090
Period	2007q1–2011q4	2007q1–2011q3	2007q1–2011q2	2007q1–2011q1	2007q1–2010q4	2007q1–2010q2	2007q1–2009q4
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Claims/Assets^2$ Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic

The table reports average marginal effects from regressions estimating the creditor bankruptcy risk associated with trade credit losses (Eq. (2) where *Claims/Assets* and *Claims/Assets*^{2} are included to measure the exposure of trade debtor failures), for a data set on a quarterly frequency covering the period 2007–2011. The models estimate the firm-failure probability in quarter $t + j$ conditional on survival in $t + j - 1$. All firm-specific variables correspond to quarter $t - 4$. The firm-specific variables are described in Table A1. The pseudo-R^2 values are calculated according to McFadden (1973). The χ^2-statistic refers to a Wald test of the null that all parameters, except the intercept, are jointly equal to zero. t-values calculated on robust standard errors, clustered at the firm-level, are reported within parenthesis. The *ROC*-measure refers to the receiving operating characteristic; gauging in-sample, overall predictive ability. ***, **,* denote statistically distinct from 0 at the 1, 5, and 10 percent level, respectively.

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