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ABSTRACT

We examine the influence of peer firms on trade credit policies of listed firms in the United States. We posit and find evidence that firms mimic their peers in formulating trade credit policies. The findings are more pronounced for firms that operate in highly competitive product markets and an uncertain information environment. Our results show that firms not only mimic peers in similar circumstances but also imitate their more and less successful peers. We find that the benefits of mimicking peers' trade credit policies increase initially, but for firms that already maintain high levels of trade credit, these benefits diminish faster as the intensity of mimicking increases. Our results are robust to different methods of selecting peers, sampling, different proxies, and estimation techniques.

1. Introduction

Trade credit is the most important source of short-term financing for firms in the United States (Petersen and Rajan, 1997; Barrot, 2016) and is responsible for global trade in excess of US\$25 trillion (Klapper et al., 2012). Non-financial and non-utility firms are the largest providers of trade credit, and in particular, can be a natural source of capital to younger and developing firms (Cosh et al., 2009). Given the economic impact of trade credit, the question of why non-financial and non-utility firms extend trade credit when more specialized financial institutions could finance trade is the subject of a growing body of literature (e.g. Petersen and Rajan, 1997; Hill et al., 2012; Biais and Gollier, 1997; Burkart and Ellingsen, 2004; Box et al., 2018).

Recent media coverage has put a spotlight on the subject of trade credit. The *New York Times* noted that an increasing number of companies were pushing their suppliers to give them up to 4 months to pay their trade credit bills (Strom, 2015). The *Wall Street Journal* singled out Black & Decker, Inc., as a big beneficiary of trade credit; the company has unlocked more than \$500 million of working capital since 2005 by delaying payment to its vendors (Shumsky and Trentmann, 2018). However, while these examples show the benefits of trade credit to these companies, the other side of the story is that longer payment periods expose the suppliers extending the trade credit to financial strain, as delayed payment drains their operating cash. In the absence of regulation to protect suppliers (Barrot, 2016), anecdotal evidence suggests that suppliers that are unable to sustain trade credit terms demanded by

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customers are able to push back only when their peers also choose to confront aggressive customer demands (Strom, 2015).

Motivated by this anecdotal evidence that a firm's trade credit actions depend on its peers, we revisit the question of why non-financial firms extend trade credit and examine the previously unexplored possibility that a firm's trade credit policies depend on peer influence. A number of studies (e.g., Foucault and Fresard, 2014; Leary and Roberts, 2014; Grennan, 2019) show that peer influence plays a vital role in shaping corporate policies, which raises the possibility that the trade credit policies of peers influence a firm's own trade credit policies. Consistent with the rivalry-based theory, as postulated by Lieberman and Asaba (2006), we expect that firms would imitate their peers to maintain competitive parity or to limit rivalry. Specifically, mimicking peers' trade credit policies can be an essential tool to enhance a firm's product market competitiveness, with the potential to increase sales and profitability.¹

To shed light on whether and how peer firms influence a firm's trade credit policies, we examine the trade credit policies of US peer firms for the period covering 1977–2016. The sample consists of 63,786 firm-year observations made up of 5,088 US firms across 153 industries. An empirical challenge in estimating peer effects derives from the reflection problem (Manski, 1993), which describes a specific form of endogeneity that arises when inferring whether average group behavior influences the behavior of an individual that belongs to the group. For example, it can be difficult to disentangle the peer effects on trade credit from common industry effects when the characteristics of the industry dictate individual trade credit policies. To address this challenge, we employ two-stage least squares (2SLS) estimation following Leary and Roberts (2014), Grennan (2019), and Adhikari and Agrawal (2018). By using instrumental variables that are independent of common industry shocks, 2SLS allows us to disentangle the common industry shocks from peer effects and thus, provides more precise and causal inferences of peer effects on trade credit policies (Leary and Roberts, 2014; Adhikari and Agrawal, 2018).

Our empirical findings, documenting evidence that peer firms influence trade credit policy, are consistent with our hypotheses. We find that a firm's accounts receivable, which we use as a measure of trade credit, is positively related to its peer firms' accounts receivable. The baseline results suggest that a one standard deviation increase in peer firms' accounts receivable results in about an 18% increase in the firm's accounts receivable. Our results are robust to alternative measures of trade policies as well as identification of peer firms. Overall, we interpret our findings as evidence that firms are sensitive and responsive to the trade credit policies of their industry peers.

Next, we examine the effects of product market competition on the peer effects of trade credit policy by partitioning our sample into subgroups based on market competition. This approach enables us to directly test the predictions of the rivalry-based theory, that mimicking is likely to be more intense in competitive industries. Our results show that peer effects increase with product market competition. This is consistent with the rivalry-based theory and is in line with Adhikari and Agrawal (2018), who find that peer firms' influence on payout policy is more pronounced for firms operating in very competitive industries. When we compare peer effects, we find that firms in competitive industries increase trade credit by at least 7%, which is about twice that when firms operate in less competitive industries. This increase in responsiveness to peer firms can be attributed to the need to match or keep abreast of the competition.

Existing evidence suggests that peer effects are characterized by the leader–follower relationship between a firm and its peers. When examining heterogeneity in peer effects, our results indicate that follower firms (which have low market share, low liquidity, and low profitability) are more sensitive to their industry leader peer firms. This evidence is consistent with both the learning motive and information-based theories (Scharfstein and Stein, 1990; Lieberman and Asaba, 2006; Leary and Roberts, 2014; Adhikari and Agrawal, 2018), where followers replicate the policies of industry leaders because they perceive them to possess superior information. However, and more tellingly, we find that industry leaders also respond to the trade credit policies of their follower peer firms. The feedback theory and the theory of predation can explain this finding (Bolton and Scharfstein, 1990; Lieberman and Asaba, 2006), highlighting the importance of trade credit as a competitive device in the product market (Fabbri and Klapper, 2016).² Thus, leaders attempt to consolidate their competitive position by adapting their policies in response to the competition, including their less successful peers.

Finally, we examine the implications of mimicking trade credit on firm value. On the one hand, mimicking peers improves a firm's competitiveness and enhances sales and profitability (Lieberman and Asaba, 2006). On the other hand, mimicking can lead to sub-optimal decisions when a firm mistakes noise for a signal (Kaustia and Rantala, 2015) or neglects its fundamentals (Fairhurst and Nam, 2020). In our setting, we find diminishing returns to mimicking peers' trade credit policies. Our results show that the benefits of mimicking peer firms' trade credit policies increase initially, but diminish as the intensity of mimicking increase. These benefits diminish faster for firms that already maintain high levels of trade credit. This finding suggests that, if firms mimic, they should actively re-evaluate their strategies in order to maximize the benefits of mimicking. Mimicking beyond the optimal level can inadvertently lead to sub-optimal policies.

This study contributes to the growing literature examining the influence of peer firms on corporate decisions. Existing empirical studies examine the influence of peer firms on a number of corporate policies, including capital structure (Leary and Roberts, 2014; Francis et al., 2016), investment (Frydman, 2015), and dividend policies (Adhikari and Agrawal, 2018; Grennan, 2019). We build on and extend this literature by focusing on trade credit policies, which form a significant and economically important part of corporate strategy. We document that the motives for mimicking reported in the literature help to explain variations in trade credit. We also shed new light on how the relationship between a firm and its peers influences trade-credit mimicking behavior. In contrast to

¹ Box et al. (2018) show that aggressive trade credit policies are associated with increased sales and profitability.

² According to the feedback theory, which is akin to the theory of predation, more successful leaders can drive less successful follower firms out of business by adopting similar financial policies (Scharfstein and Stein, 1990; Leary and Roberts, 2014).

existing studies (e.g., [Leary and Roberts, 2014](#); [Adhikari and Agrawal, 2018](#)), our findings suggest that peer effects are associated with not only follower firms imitating leader firms but also both follower and leader firms imitating each other's trade credit policies. We attribute these findings to the multifaceted roles that trade credit plays as a tool for fighting competition and as a means of alleviating product market and capital market imperfections.

Our study also contributes to the trade credit literature, showing that peer effects play an important role in shaping trade credit policies. There is a marked difference between this study and previous research on trade credit. The prior findings focus on how a firm's internal characteristics determine its trade credit policies (e.g., [Petersen and Rajan, 1997](#); [Biais and Gollier, 1997](#); [Burkart and Ellingsen, 2004](#), among others). Our study provides evidence of peer effects on trade credit policy. A recent study by [Chod et al. \(2019\)](#) asserts that customers, especially cash-constrained customers, exploit competition between suppliers for favorable trade credit terms. The difference between our study and [Chod et al. \(2019\)](#) is that we focus on how a given firm is shaped by the trade credit policies of its peers rather than how customers influence a given firm's policies. Overall, the interactions between firms explain trade credit policies beyond the factors already identified in the literature.

Our findings are relevant to academic researchers and have policy implications. Academic researchers have long explored the determinants of trade credit, which continues to be an important source of business financing ([Cosh et al., 2009](#); [Barrot, 2016](#); [Box et al., 2018](#)). We find that learning from peers matters for trade credit decisions, especially among small and young firms as well as firms in highly competitive environments. In some instances, this may increase welfare, as less informed firms can benefit from the actions of more informed peers. However, inefficient mimicking and diminishing returns to trade credit may occur, leading to information externalities if firms ignore their own private signals or have little understanding of their markets when they mimic peer trade credit policies ([Banerjee, 1992](#); [Bikhchandani et al., 1992](#); [Hirshleifer and Teoh, 2003](#); [Bursztyn et al., 2014](#)). In this case, regulators that have mandates to protect investors, such as the Securities Exchange Commission (SEC), may wish to intervene to require additional disclosures of a firm's trade credit practices to ensure that trade credit practices do not introduce distortions in capital markets.

The rest of the paper is organized as follows. [Section 2](#) reviews the related literature and formulates hypotheses. [Section 3](#) discusses the data. [Section 4](#) explains our empirical methodology, including the construction, relevance, and validity of our instrument. [Section 5](#) presents the empirical results. [Section 6](#) presents robustness tests. [Section 7](#) concludes.

2. Background and hypotheses

2.1. Peer effects

Some emerging literature highlights the role of peer effects in a firm's corporate financial policies. Identifying peer effects in corporate financial policies is theoretically intuitive, given that a substantial body of theoretical research identifies peer effects in a number of other corporate policies, including product pricing, product output, and labor practices (see [Leary and Roberts, 2014](#)). Moreover, survey evidence in [Graham and Harvey \(2001\)](#) highlights the importance of peer firm financing decisions for a given firm's financing decisions. Building on these findings, recent studies report significant peer effects on financial policies, such as capital structure ([Leary and Roberts, 2014](#); [Francis et al., 2016](#)), cash holdings ([Chen et al., 2019](#)), and dividend policy ([Adhikari and Agrawal, 2018](#); [Grennan, 2019](#)).

Peer firm imitation is a rational decision for strategic reasons. [Leary and Roberts \(2014\)](#), for example, argue that industry interactions between a firm and its peers influence the firm's financial policy. In other words, the industry interactions indicate that the policies of peers have both direct and indirect impacts on the focal firm. Furthermore, survey evidence of chief financial officers confirms that firms follow the financial policies of their peers ([Graham and Harvey, 2001](#)). In the context of cash policy, [Benoit \(1984\)](#) asserts that a firm's cash policy can influence entry into new markets or the capacity to expand. Thus, adopting a cash policy of peers allows a firm to compete and tap into the prospects of the industry. Even though peer effects may be motivated by strategic purposes, it is also possible for a firm to misinterpret peers' decisions. For example, [Kaustia and Rantala \(2015\)](#) argue that firms can mistake noise for a signal and overreact to peers' policy and outcomes. This effect could explain why peer effects might not generate the intended beneficial effects. Despite this potential anomaly, peer effects could still constitute a more accessible source of information for corporate managers in formulating corporate financial policies. We extend this literature by examining a firm's response to the trade credit policies of its industry peers.

2.2. Trade credit

Trade credit, the most important source of short-term financing for firms in the United States ([Petersen and Rajan, 1997](#); [Barrot, 2016](#)), represents an agreement between a supplier and customer for the customer to purchase goods and services on credit (i.e., without immediate payment). Trade credit policy encompasses the decision to extend trade credit and the specific terms associated with the credit. The terms of credit include the amount of credit, the length of time (usually in days) that a customer has to make a payment, and the potential discounts that a customer receives for making a payment within a specified number of days.

Prior literature explores why suppliers, rather than financial institutions, are the largest providers of these short-term loans and documents that suppliers have financing advantages over financial institutions. Such advantages include reducing the effects of asymmetric information associated with customers by deploying their comparative advantage over financial institutions in acquiring information, evaluating buyers' creditworthiness ([Smith, 1987](#); [Biais and Gollier, 1997](#)), enforcing credit contracts and mitigating buyers' opportunistic behavior ([Burkart and Ellingsen, 2004](#); [Fabbri and Menichini, 2010](#); [Chod, 2016](#)), and providing liquidity

insurance to constrained customers (Ng et al., 1999; Wilner, 2000; Cuat, 2007). Moreover, suppliers derive operational and competitive benefits from extending trade credit. For example, trade credit represents an implicit guarantee of product quality (Lee and Stowe, 1993; Long et al., 1993; Petersen and Rajan, 1997), enhances favorable price discrimination for risky customers without direct use of prices (Brennan et al., 1988), and improves sharing of demand risk (Kouvelis and Zhao, 2012; Yang and Birge, 2017). Moreover, Cosh et al. (2009) suggest that suppliers can be a natural source of capital to younger and developing firms and this in turn allows suppliers to secure a supply chain to support the development of their own products.

Dass et al. (2015) and Fabbri and Klapper (2016) argue that suppliers use trade credit to gain a competitive advantage in the product market. Since industry competition undermines the relative bargaining power of suppliers, firms that face competitive pressures have greater incentives to provide trade credit, and possibly imitate the trade credit terms of the market leaders to catch up. Overall, trade credit policy is a channel through which firms can achieve improvements in the level of competitiveness in the product market against its rivals. Firms can adopt more favorable trade credit terms to establish a reputation and guarantee product quality. Over time, these firms establish relationships with their customers, enabling them to win new customers in competitive markets. This effect culminates in increased sales and profitability (Martínez-Sola et al., 2013; Box et al., 2018), enhancing the supplier's competitive position in the market. Accordingly, to enhance a firm's competitive positioning in its industry, it is plausible that the firm would mimic the trade credit policies of its peers.

2.3. Hypotheses

To test whether and how firms mimic their peers' trade credit policies, we develop our hypotheses based on existing theories on peer effects. Lieberman and Asaba (2006) highlight that mimicking (or imitation) is a common form of behavior that arises in a variety of business domains, such as the introduction of new products and processes and the adoption of managerial methods and organizational forms.

Firms may mimic to avoid falling behind or to stay ahead of their rivals. As opportunities arise from sudden environmental shifts and by competitive threats of rivals, mimicking rivals' actions can neutralize threats to a firm's competitive position (Cabral, 2002; Ross and Sharapov, 2015; Lieberman and Asaba, 2006; Sharapov and Ross, 2019). Lieberman and Asaba (2006) identify this as a rivalry-based theory of mimicking behavior, which postulates that firms imitate others to maintain competitive parity or limit rivalry. This rivalry-driven mimicking behavior manifests among firms of similar size and resources competing in the same market and operating in an environment in which information is readily available (Lieberman and Asaba, 2006; Adhikari and Agrawal, 2018).

In the context of trade credit, Box et al. (2018) show that aggressive trade credit policies are positively associated with operating performance. Accordingly, firms may mimic their peers' trade credit policies in order to stay competitive. For example, all else being equal, if a firm gives its customers 10 days to pay trade credit bills, but observes its rivals giving 30 days, then the firm might mimic its rivals by extending its credit terms in order to compete for customers in the same industry that would find the rivals' longer 30 days more attractive. Conversely, if rivals tighten their trade credit terms, the firm might also tighten its own credit terms, as this would allow the firm to become more competitive by generating more cash in a shorter period of time.

Accordingly, we posit that firms are more inclined to mimic the trade credit policies of their industry peers to maintain competitive parity or to limit rivalry in their industry. Thus, we derive our first hypothesis as follows:

Hypothesis 1. *Firms imitate the trade credit policies of their industry peers.*

Lieberman and Asaba (2006) also argue that imitation increases in competitive markets in line with the rivalry-based theory. Even though competition is related to peer effects, the two concepts are distinct (Bird et al., 2018). On the one hand, peer groups and the dynamics between peer firms deal with the interactions and interrelationships between similar firms within the same industry. On the other hand, a firm's ability to determine the price, quality, and nature of the product in the marketplace defines its market power and the degree of competitive threats (Kubick et al., 2015). Fabbri and Klapper (2016) document that suppliers in more competitive industries tend to extend more trade credit.

We argue that intense competition in the product market increases the incentives to imitate the behavior of industry peers. In other words, imitating the trade credit policies of peers becomes more pronounced in order to neutralize competitive pressures, and potentially leads to increased sales and profitability (Martínez-Sola et al., 2013; Box et al., 2018). Firms facing less competition have limited incentives to imitate their peers' trade credit policies. However, the need to follow peer behavior increases in competitive markets with similar products, because it is difficult to achieve product differentiation in such markets (Adhikari and Agrawal, 2018). Thus, suppliers can employ trade credit to undercut industry competitors trading in substitute products. In summary, the incentives to respond to the decisions of peers increase with the degree of competitive pressures in the market. Thus, we derive our second hypothesis:

Hypothesis 2. *The peer effects of trade credit increase with the level of industry competition.*

Information-based theories of imitation in economics and other fields postulate that in environments of uncertainty and ambiguity, firms are more likely to take actions based on information implicit in the actions of other firms (Lieberman and Asaba, 2006; Adhikari and Agrawal, 2018). In particular, Lieberman and Asaba (2006) suggests that firms imitate peers that are perceived to have superior information. Information is a key driver of trade credit. Non-financial firms are the largest suppliers of trade credit because of their informational advantage over financial institutions or other potential providers of external finance (Smith, 1987; Biais and Gollier, 1997).

Although firms have an informational advantage over financial institutions, firms still incur costs of acquiring and/or processing information. In particular, transaction costs associated with trade credit information and monitoring are incurred when informational asymmetries exist between buyer and seller (Ng et al., 1999). For this reason, trade credit terms are viewed as contractual solutions to informational problems present between sellers and buyers concerning product quality and buyer creditworthiness (Smith, 1987; Ng et al., 1999; Pike et al., 2005). Accordingly, when information asymmetry is high, firms likely have the incentives to mimic their peers perceived to have better information. In such cases, peer actions are a source of valuable information about the creditworthiness of buyers and the pattern of industry financial activity. Thus, firms that operate in an uncertain environment closely monitor their peers and are more likely to adopt the trade credit policies of their industry rivals.

Hypothesis 3. *The peer effects of trade credit increase when firms operate in a high asymmetric information environment.*

The nature of the relationship between a firm and its peers determines the extent and the direction of mimicking. Whereas firms with similar characteristics mimic to maintain competitive parity, firms with different fundamentals are driven by information effects to imitate (Lieberman and Asaba, 2006; Adhikari and Agrawal, 2018). Consistent with the information-based theory, followers mimic leaders, which are perceived to possess better information about product markets. Adhikari and Agrawal (2018) define followers (leaders) as firms that are smaller (larger), younger (older), and less (more) tangible. Concerning trade credit, Wilson and Summers (2002) posit that smaller firms incur higher costs than larger firms of funding trade credit with limited economies of scale to diversify their source of financing. Hence, dominant customers can easily exploit smaller firms and dictate the terms of trade credit. However, smaller and younger firms may have the most incentive to use trade credit extension to establish a reputation, guarantee product quality, and enhance product marketability. In other words, trade credit acts as a channel to facilitate sales, especially of suppliers with smaller market shares (Hill et al., 2012).

Two motives underscore the mimicking behavior among firms based on their characteristics. First, the learning motive suggests that followers with the greatest need to build a reputation are more likely to mimic the behavior of leaders (Scharfstein and Stein, 1990; Leary and Roberts, 2014). Second, feedback theory suggests that leaders mimic the financial policies of followers either to defend their lead in the market or to drive them out of business (Brander and Lewis, 1986; Bolton and Scharfstein, 1990; Sharapov and Ross, 2019). For instance, Giannetti et al. (2020) argue that suppliers that face a fringe of potential new entrants provide cheap trade credit to ease competition for customers. This supplier can offer favorable trade credit to customers with high bargaining power to limit competition, and generate strong demand and profits from customers with low bargaining power. Accordingly, we do not state a directional prediction, but instead, provide the following null hypothesis.

Hypothesis 4. *Followers (leaders) are not likely to imitate the trade credit policies of their industry leaders (followers).*

The extent to which firms mimic their peer firms' trade credit policies can generate benefits or costs. Thus far, our hypotheses suggest that firms mimic their peers to stay competitive or to take advantage of superior information. In these cases, mimicking can benefit the firms. If a firm mimics to increase trade credit, it could improve the firm's operating performance (Box et al., 2018).

However, costs may arise, because firms may ignore their own private information or competitive advantages (Hirshleifer and Teoh, 2003). For example, in other financial policy decisions, Fairhurst and Nam (2020) suggest that mimicking may cause managers to avoid the effort required to execute value-enhancing strategies. The same outcome is possible with trade credit policies. It is also possible for firms to mistake noise for a signal and overreact to peers' actions (Kaustia and Rantala, 2015). Therefore, the beneficial effects of mimicking may depend on a firm's accurate interpretation of the actions of its peers as well as its levels of trade credit. Mimicking by firms that already maintain high levels of trade credit might result in lower market values. For instance, Martínez-Sola et al. (2013) and Hill et al. (2015) show diminishing returns to extending trade credit beyond an optimal level. Their evidence suggests that trade credit increases (decreases) firm value at low (high) levels.

Accordingly, based on the notion that mimicking can yield benefits to the firm but that these potential benefits diminish as the intensity of mimicking increases, we test the following proposition.

Hypothesis 5. *The benefits of mimicking diminish as the intensity of mimicking increases.*

However, these hypotheses might not hold. Firms that experience negative liquidity shocks would be less inclined to extend trade credit to their credit-constrained buyers because of adverse effects on their working capital (Amberg et al., 2016). Thus, these firms are less likely to imitate their peers' trade credit policies. In addition, some firms might not want to bear the risks of delayed payments associated with trade credit. Murfin and Njoroge (2015) find that delayed payments by large retail buyers are associated with significant under-investment in new plants and equipment at the supplier level. To mitigate these negative outcomes, firms may moderate their trade credit policies regardless of their peer firms' policies. Thus, the effects of peers on a firm's trade credit policies are not obvious, making this an open empirical research question.

3. Data

Our sample is drawn from the Compustat database for the financial statement variables and the Center for Research in Security Prices for stock returns, covering the period 1977–2016. The starting date of our analysis is purely dictated by data availability. As is standard in the literature, we apply several filters to the data. We exclude financial firms (Standard Industrial Classification, SIC code

6000–6999) and utility firms (SIC code 4900–4999), because these industries are highly regulated. Furthermore, we exclude firms with negative equity and missing data on key variables used in this study. To reduce the effects of outliers, we winsorize all continuous variables at the top and bottom 1%. We describe in detail each of the variables used in Appendix A. We define peer groups based on three-digit SIC industry groups.³ Our final sample consists of 63,786 firm-year observations for 5,088 firms across 153 industries. The number of observations in the analyses varies depending on the restrictions imposed for different variable measurements and set of control variables.

4. Methodology

4.1. Baseline estimation model

To investigate peer effects on trade credit, we estimate the following model of Leary and Roberts (2014):

$$y_{ijt} = \alpha + \beta \bar{y}_{-ijt} + \gamma \bar{X}_{-ijt-1} + \lambda' X_{ijt-1} + \mu_j + \nu_t + \epsilon_{ijt} \quad (1)$$

where y_{ijt} is the trade credit for firm i in industry j at time t , α is a constant, and β , γ' and λ' are the vectors of coefficients to be estimated. \bar{y}_{-ijt} is peer firms' average excluding firm i . \bar{X}_{-ijt-1} and X_{ijt-1} are vectors of peer firms' average and firm-specific characteristics, respectively. μ_j and ν_t are industry and year fixed effects, respectively. Finally, ϵ_{ijt} is the firm-year specific error term. Consistent with Leary and Roberts (2014), we assume that ϵ_{ijt} is correlated within firms and heteroskedastic. As discussed in the following subsection 4.2, we use peer idiosyncratic return shocks as an instrument for the endogenous peer firm average trade credit. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the observations for firm i . The vectors \bar{X}_{-ijt-1} and X_{ijt-1} include the factors found to be determinants of trade credit in the literature (e.g., Frank and Goyal, 2009; Oztekin, 2015).

4.2. Instrument for 2SLS estimation

Studies of peer effects are subject to endogeneity concerns. The primary issue, referred to as the “reflection problem” (Manski, 1993), is the difficulty of disentangling the peer effects on trade credit from common industry effects when the characteristics of the industry dictate individual trade credit policies. In other words, endogeneity arises in the attempt to infer whether the average group behavior influences the behavior of an individual who belongs to the group. Moreover, endogeneity arises from the selection of firms into peer groups or an omitted common factor and identifying whether the response to peer effects operates through their actions or characteristics (Leary and Roberts, 2014). To address the endogeneity concerns, we estimate 2SLS following prior studies (Leary and Roberts, 2014; Adhikari and Agrawal, 2018). By dealing with endogeneity issues, we are better able to analyze the extent to which the actions stemming from peer firms' policy choices influence a focal firm's trade credit policy beyond the effects of the firm characteristics.

Following Leary and Roberts (2014) and Adhikari and Agrawal (2018), we use peer firms' equity idiosyncratic return shock as an instrument in the 2SLS estimation. Specifically, we use the lagged idiosyncratic stock returns of peer firms as instrumental variables to proxy for peer firm average trade credit. We estimate the idiosyncratic stock returns using the augmented Carhart (1997) model as follows⁴:

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^M (RM_t - RF_t) + \beta_{ijt}^{SMB} \times SMB_t + \beta_{ijt}^{HML} \times HML_t + \beta_{ijt}^{MOM} \times MOM_t + \beta_{ijt}^{IND} (\bar{R}_{-ijt} - RF_t) + \eta_{ijt} \quad (2)$$

where R_{ijt} is the total stock return for firm i in industry j over month t , $RM_t - RF_t$ is the excess market return, SMB_t is the size factor, HML_t is the book-to-market factor, MOM_t is the momentum factor, $\bar{R}_{-ijt} - RF_t$ is the excess return on an equally weighted industry portfolio (where the industry is defined by the three-digit SIC code), excluding firm i 's return, and η_{ijt} is the error term.

We estimate Eq. (2) on a rolling annual basis using monthly returns. At a minimum, we require each firm to have at least 24 months of historical returns data and use up to 60 months of data for the estimations. Using the estimated coefficients from Eq. (2) for the previous year ($t - 1$) and the monthly factor returns for the current year (t), we use Eq. (3) to compute expected return and Eq. (4) for the idiosyncratic return as follows:-

$$\begin{aligned} \text{Expected Return} \equiv \widehat{R}_{ijt} &= \widehat{\alpha}_{ijt} + \widehat{\beta}_{ijt}^M (RM_t - RF_t) + \widehat{\beta}_{ijt}^{SMB} \times SMB_t \\ &+ \widehat{\beta}_{ijt}^{HML} \times HML_t + \widehat{\beta}_{ijt}^{MOM} \times MOM_t \\ &+ \widehat{\beta}_{ijt}^{IND} (\bar{R}_{-ijt} - RF_t) \end{aligned} \quad (3)$$

$$\text{Idiosyncratic Return} \equiv \widehat{\eta}_{ijt} = R_{ijt} - \widehat{R}_{ijt} \quad (4)$$

³ We also use two-digit SIC codes and Fama and French's 48 industry group classification as alternative peer group definitions in the robustness tests.

⁴ Our approach is in line with that of Adhikari and Agrawal (2018), who examine peer effects on dividend payout policies.

Table 1
Stock return regressions.

| Variables | Mean | Median | SD |
|------------------------------|--------|--------|-------|
| $\hat{\alpha}_{ijt}$ | 0.006 | 0.006 | 0.019 |
| $\hat{\beta}_{ijt}^M$ | 0.533 | 0.578 | 1.010 |
| $\hat{\beta}_{ijt}^{SMB}$ | 0.079 | 0.088 | 1.086 |
| $\hat{\beta}_{ijt}^{HML}$ | 0.479 | 0.425 | 1.234 |
| $\hat{\beta}_{ijt}^{MOM}$ | -0.070 | -0.050 | 0.738 |
| $\hat{\beta}_{ijt}^{IND}$ | 0.443 | 0.334 | 0.782 |
| Obs per Regression | 58 | 60 | 7 |
| R ² | 0.250 | 0.226 | 0.164 |
| Monthly Return | 0.015 | 0.013 | 0.045 |
| Expected Monthly Return | 0.016 | 0.015 | 0.035 |
| Idiosyncratic Monthly Return | -0.001 | -0.002 | 0.041 |

The table presents the summary statistics estimated from the following model:

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^M (RM_t - RF_t) + \beta_{ijt}^{SMB} \times SMB_t + \beta_{ijt}^{HML} \times HML_t + \beta_{ijt}^{MOM} \times MOM_t + \beta_{ijt}^{IND} (\bar{R}_{-ijt} - RF_t) + \eta_{ijt}$$

where R_{ijt} is the total stock return for firm i in industry j over month t , $RM_t - RF_t$ is the excess market return, SMB_t is the size factor, HML_t is the book-to-market factor, MOM_t is the momentum factor, $\bar{R}_{-ijt} - RF_t$ is the excess return on an equally weighted industry portfolio (where the industry is defined by the three-digit SIC code), excluding firm i 's return, and η_{ijt} is the error term. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are winsorized at the lower and upper first percentiles.

We calculate the annual idiosyncratic return shock by taking the geometric average of the monthly idiosyncratic returns from Eq. (4). Our instrument, the average peer idiosyncratic return shock, is calculated similarly to the average peer firm-specific variables in Eq. (1) discussed above.⁵

4.3. Peer firm return shock characteristics

Table 1 presents the output of the stock return regressions. The factor regressions load positively on market, size, book-to-market, and industry beta and negatively on the momentum factor. Overall, these factors remove most of the systematic variation in stock returns. The results in Table 0 also show that the idiosyncratic component accounts for a significant portion of the variation in stock prices with mean R-squared of 25%. Similar to Leary and Roberts (2014), this result suggests that the average total return of other firms in an industry may provide a less noisy measure of the trade credit opportunities facing each firm than their stock return or market-to-book ratios. The average monthly return is 1.5%, and the average expected monthly return is 1.6%. The average idiosyncratic monthly return is -0.1%, which by construction should be zero without loss of observations in the data-cleaning process.

4.4. Validity and relevance of the instrument

To support the validity of our instrumental variable, we discuss and present diagnostic tests for two conditions that an instrument must satisfy to be valid, namely, the relevance criterion and the exclusion restriction. To satisfy the relevance criterion, an instrument should be strongly correlated with the endogenous outcome variable. In our case, the peers' return shock should be correlated with the peers' trade credit policy. For the exclusion restriction, the instrument should not have a direct effect on the dependent variable, which in our case is the firm-specific trade credit. We expect the instrument to work as follows: a peer firm experiences a unique shock and the shock causes the peer firm to take action on its trade credit policies (endogenous variable). In turn, upon observing the actions of the peers on trade credit, the focal firm imitates by taking action on its own trade credit (dependent variable in our study).

We first discuss the relevance criterion, on whether the instrument predicts trade credit policies. There is empirical evidence of a significant relationship between stock returns and trade credit (Hill et al., 2012; Albuquerque et al., 2015; Goto et al., 2015). For example, Abdulla et al. (2017) argue that access to public markets enables public firms to advance more trade credit than unlisted firms can. Similarly, Martínez-Sola et al. (2013) find a significant non-monotonic relationship between firm value and trade credit. Hill et al. (2015) also find a

⁵ For robustness, we also calculate the average peer idiosyncratic risk as an additional instrument. This is calculated as the standard deviation of the idiosyncratic returns from Eq. (4) in line with Adhikari and Agrawal (2018). Our unreported results remain qualitatively similar when we include this average peer idiosyncratic risk as an additional instrument.

significant but diminishing and heterogeneous nexus between excess returns and trade credit. For the peer firms in our sample, we find that peers' average idiosyncratic return shock is partially and sufficiently strongly correlated with their trade credit policies, even after controlling for the other independent variables. Thus, we confirm the relevance condition of our instrumental variable. In addition, for all our estimations, the Cragg–Donald F-statistic (Cragg and Donald, 1993) is large, which provides further evidence of the relevance of our instrument.

Next, we discuss the exclusion restriction that the instrument does not have a direct effect on the dependent variable. In measuring the idiosyncratic return shock, we purge common factors using the Carhart four-factor model (Carhart, 1997) and the excess returns on an equally weighted industry portfolio, which excludes the focal firm (where the industry is defined by the three-digit SIC code). The Carhart four-factor model that we use performs relatively well in separating common and firm-specific shocks as documented in the asset pricing literature (see Rath and Durand, 2015; Adhikari and Agrawal, 2018). Our inclusion of the excess returns on a three-digit SIC code equally weighted industry portfolio, which excludes the focal firm, takes out any component of the return shocks that is common to the industry and market. This separates out industrial and market level co-movements in equity prices, thereby, making our instrument orthogonal to common market and industry risk. Based on this adjustment to the Carhart four-factor model (Carhart, 1997), we consider that the exclusion restriction to be satisfied, as the peer idiosyncratic shocks by construction do not directly affect the firms trade credit policies. Therefore, the effect is likely to be indirect through other peer firms. To ensure that we isolate the trade credit channel, which is the focus of our study, we include in all estimations of Eq. (1) peer averages of firm-specific variables as controls for any other channel through which the indirect effects may occur.

To gain further confidence in our instrumental variable approach, we present in Table 4 the estimation results of Eq. (1), which relates peer equity residuals to firm-specific and peer firms' average characteristics. For the contemporaneous regression, Panel A, we find that our instrument is significantly linked to only debt and size, while Panel B, for the one-period-lag model, it predicts cash, debt, and size. To reduce concerns that firms observe these factors, we include other peer average and firm-specific factors as control variables in all our regression models. In addition, we find very low correlations of 0.020 and -0.001 for the relationship between contemporaneous peers' idiosyncratic return shock and the firm's equity idiosyncratic return shock as well as between the peers' idiosyncratic return shock and the lagged firm's equity idiosyncratic return shock, respectively. This result is in line with Leary and Roberts (2014) and suggests that the exclusion restrictions are not violated in our case. To allay concerns relating to any residual correlation between our instrument and firm-specific characteristics, we include the firm's equity idiosyncratic return shock in all our estimations of Eq. (1). Later in the empirical and robustness sections, we report that our instrument performs well, as it positively predicts peer average trade credit and the F-Statistic of the first stage is large and significant at the 1% level.⁶

4.5. Summary statistics

Table 2 provides the summary statistics of both peer-firm and firm-specific characteristics. The mean accounts receivable is 0.184 for the firm and peer firm, which, according to our measure of accounts receivable, represents 18.4% of total assets. The standard deviation of firm-specific accounts receivable is 0.121, whereas that of the peer firms is 0.080. The maximum firm-specific and peer firm accounts receivable represent 59.3% of total assets. This is higher than the mean cash holdings of 0.153.

Overall, peer firm averages for all the variables are similar to individual firm averages, as expected, but the standard deviations of peer firm averages are consistently lower than those of individual firms.⁷ The average annual idiosyncratic return shock is -4.7% for both firm and peer firms, which is different from 0 mainly because the return shocks are annualized by compounding the monthly shocks. The standard deviation idiosyncratic monthly returns are 37.9% and 11.8% for firm and peer firms, respectively.

Table 3 presents partial correlations between firm-specific average trade credit (accounts receivable and payable) and peer firm average trade credit, as well as other firm-specific characteristics. We find that the correlation between firm accounts receivable and peer firm average accounts receivable is 0.601 and significant at the 1% level. This result gives preliminary evidence of the positive effects on peer accounts receivable on a firm's policy on accounts receivable. However, this does not tell the full story, as it does not account for other important factors that explain trade credit policies. Therefore, we thoroughly explore peer effects on trade credit using the econometric model in Section 5, and account for the impact of other variables that determine trade credit policy. The correlations between firm average equity shocks and firm i 's characteristics are all low; the highest absolute correlation coefficient is 0.089. There are small but insignificant intra-industry correlations in returns.

The results in Table 4 examine the correlations with both contemporaneous and one-period lead effects to determine whether our measure contains information about current or future firm i 's characteristics, in line with both Leary and Roberts (2014) and Adhikari and Agrawal (2018).⁸ In other words, the returns model allows us to detach the effect of a firm's stock price informativeness on trade credit policy such that we observe only the effects associated with firm characteristics and actions related to the trade credit decisions of peers. The results reveal three statistically significant coefficients among firm i characteristics in the contemporaneous specification and the one period-lead specification. However, the small economic magnitudes of the coefficient estimates make their effects tenuous. Thus, the peer firm equity shocks contain less significant information related to firm i 's current or near-future observable trade credit determinants. These results highlight the reliability of the equity shocks as an instrument used to estimate the 2SLS model.

⁶ The F-statistic is greater than the rule of thumb of 10 in the first stage (Staiger and Stock, 1997; Stock et al., 2002; Nason and Patel, 2016).

⁷ The results are similar to those reported by Leary and Roberts (2014) and Adhikari and Agrawal (2018).

⁸ Leary and Roberts (2014) argue that correlation with the characteristics is not problematic although economically large associations between the measure and observable firm characteristics would raise concerns about the extent to which our measure may be correlated with unobservable factors. The returns model should remove common variation among firms' returns to reduce this potential bias.

Table 2
Summary statistics.

| Panel A: Full sample | | | | | | | | | | |
|------------------------------------|-------------------|------------|---------------|------------|------------|------------|------------|------------|--------------|------------|
| Variables | N | Mean | SD | Min | p25 | Median | p75 | Max | | |
| Firm specific characteristics | | | | | | | | | | |
| AR_{ijt} | 63,786 | 0.184 | 0.121 | 0.002 | 0.094 | 0.169 | 0.253 | 0.593 | | |
| AP_{ijt} | 63,786 | 0.089 | 0.070 | 0.005 | 0.041 | 0.071 | 0.116 | 0.379 | | |
| $Cash_{ijt}$ | 63,786 | 0.153 | 0.173 | 0.000 | 0.025 | 0.084 | 0.221 | 0.761 | | |
| $Debt_{ijt}$ | 63,786 | 0.200 | 0.170 | 0.000 | 0.040 | 0.180 | 0.313 | 0.668 | | |
| $Size_{ijt}$ | 63,786 | 5.620 | 1.958 | 1.645 | 4.185 | 5.500 | 6.941 | 10.589 | | |
| PPE_{ijt} | 63,786 | 0.289 | 0.216 | 0.012 | 0.120 | 0.235 | 0.400 | 0.892 | | |
| SG_{ijt} | 63,786 | 0.093 | 0.226 | -0.506 | -0.014 | 0.073 | 0.183 | 1.013 | | |
| ROA_{ijt} | 63,786 | 0.114 | 0.126 | -0.407 | 0.069 | 0.128 | 0.184 | 0.386 | | |
| $EShock_{ijt}$ | 63,786 | -0.047 | 0.379 | -0.790 | -0.278 | -0.083 | 0.120 | 1.484 | | |
| Peer firm averages | | | | | | | | | | |
| $P \cdot AR_{ijt}$ | 63,786 | 0.184 | 0.080 | 0.006 | 0.132 | 0.186 | 0.237 | 0.593 | | |
| $P \cdot AP_{ijt}$ | 63,786 | 0.089 | 0.040 | 0.009 | 0.065 | 0.084 | 0.103 | 0.379 | | |
| $P \cdot Cash_{ijt}$ | 63,786 | 0.153 | 0.097 | 0.003 | 0.078 | 0.123 | 0.213 | 0.460 | | |
| $P \cdot Debt_{ijt}$ | 63,786 | 0.200 | 0.083 | 0.000 | 0.137 | 0.191 | 0.250 | 0.570 | | |
| $P \cdot Size_{ijt}$ | 63,786 | 5.620 | 0.968 | 2.208 | 4.922 | 5.541 | 6.189 | 9.940 | | |
| $P \cdot PPE_{ijt}$ | 63,786 | 0.289 | 0.174 | 0.013 | 0.168 | 0.240 | 0.354 | 0.843 | | |
| $P \cdot SG_{ijt}$ | 63,786 | 0.093 | 0.093 | -0.440 | 0.044 | 0.095 | 0.144 | 0.736 | | |
| $P \cdot ROA_{ijt}$ | 63,786 | 0.114 | 0.053 | -0.204 | 0.082 | 0.114 | 0.150 | 0.355 | | |
| $P \cdot EShock_{ijt}$ | 63,786 | -0.047 | 0.118 | -0.638 | -0.124 | -0.055 | 0.018 | 1.041 | | |
| Industries | 153 | | | | | | | | | |
| Firms | 5088 | | | | | | | | | |
| Panel B: Cross-industry variations | | | | | | | | | | |
| Variables | Non-manufacturing | | Manufacturing | | Technology | | Durables | | Non-durables | |
| | AR_{ijt} | AP_{ijt} | AR_{ijt} | AP_{ijt} | AR_{ijt} | AP_{ijt} | AR_{ijt} | AP_{ijt} | AR_{ijt} | AP_{ijt} |
| N | 24,942 | 24,942 | 38,844 | 38,844 | 16,039 | 16,039 | 12,743 | 12,743 | 9265 | 9265 |
| Firms | 2194 | 2194 | 2894 | 2894 | 1235 | 1235 | 926 | 926 | 672 | 672 |
| Mean | 0.171 | 0.092 | 0.193 | 0.088 | 0.183 | 0.076 | 0.210 | 0.095 | 0.183 | 0.098 |
| SD | 0.127 | 0.064 | 0.184 | 0.075 | 0.174 | 0.061 | 0.203 | 0.084 | 0.170 | 0.086 |
| Min | 0.149 | 0.085 | 0.098 | 0.059 | 0.102 | 0.060 | 0.093 | 0.054 | 0.093 | 0.058 |
| p25 | 0.002 | 0.005 | 0.002 | 0.005 | 0.002 | 0.005 | 0.002 | 0.005 | 0.002 | 0.005 |
| Median | 0.049 | 0.032 | 0.123 | 0.048 | 0.106 | 0.036 | 0.147 | 0.057 | 0.115 | 0.058 |
| p75 | 0.258 | 0.124 | 0.251 | 0.113 | 0.246 | 0.097 | 0.261 | 0.120 | 0.241 | 0.123 |
| Max | 0.593 | 0.379 | 0.593 | 0.379 | 0.593 | 0.379 | 0.593 | 0.379 | 0.593 | 0.379 |

The table presents the summary statistics for all the variables used. The firm-specific characteristics are defined as follows: AR_{ijt} is accounts receivable to total assets, AP_{ijt} is accounts payable to total assets, $Cash_{ijt}$ is cash and cash equivalent to total assets, $Debt_{ijt}$ is debt to total assets, $Size_{ijt}$ is size (logarithm of total assets), PPE_{ijt} is fixed assets to total assets, SG_{ijt} is sales growth, ROA_{ijt} is profitability (earnings before interest and tax to total assets) and $EShock_{ijt}$ is idiosyncratic stock returns. The peer firm's average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot AP_{ijt}$ is peer accounts payable to total assets, $P \cdot Cash_{ijt}$ is peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt}$ is peer debt to total assets, $P \cdot Size_{ijt}$ is peer size (logarithm of total assets), $P \cdot PPE_{ijt}$ is peer fixed assets to total assets, $P \cdot SG_{ijt}$ is peer sales growth, $P \cdot ROA_{ijt}$ is peer profitability (earnings before interest and tax to total assets) and $P \cdot EShock_{ijt}$ is peer idiosyncratic stock returns. The peer firm's average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles.

5. Empirical results

We examine peer effects on trade credit in Section 5.1 based on a full sample using several variants of Eq. (1). We extend the analysis by examining the effect of product market competition on peer effects in Section 5.2. In Section 5.3, we investigate the effects of industry information environment on peer effects. Finally, we explore the effects of heterogeneity on peer effects in Section 5.4.

5.1. Peer effects on trade credit

Table 5 presents the results of estimating Eq. (1), which relates trade credit to peer firm and firm-specific characteristics. This result tests our initial hypothesis (Hypothesis 1) that peer firms' trade credit policy affects a focal firm's trade credit policy beyond the factors documented in the literature. We estimate our base model using FE estimation, whose output is presented in Columns 1–4. The dependent variable (AR_{ijt}) is the firm's accounts receivable and the independent variable is the peer firms' accounts receivable

Table 3
Correlations.

| # | Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|------|--------------------|-----------|-----------|-----------|-----------|-----------|-----------|----------|----------|----------|----------|------|
| (1) | AR_{ijt} | 1 | | | | | | | | | | |
| (2) | AP_{ijt} | 0.359*** | 1 | | | | | | | | | |
| (3) | $P \cdot AR_{ijt}$ | 0.601*** | 0.158*** | 1 | | | | | | | | |
| (4) | $P \cdot AP_{ijt}$ | 0.182*** | 0.491*** | 0.316*** | 1 | | | | | | | |
| (5) | $Cash_{ijt}$ | -0.214*** | -0.256*** | -0.030*** | -0.178*** | 1 | | | | | | |
| (6) | $Debt_{ijt}$ | -0.092*** | 0.031*** | -0.120*** | 0.016*** | -0.466*** | 1 | | | | | |
| (7) | $Size_{ijt}$ | -0.199*** | -0.085*** | -0.214*** | 0.003 | -0.166*** | 0.183*** | 1 | | | | |
| (8) | PPE_{ijt} | -0.373*** | -0.093*** | -0.398*** | -0.064*** | -0.391*** | 0.322*** | 0.185*** | 1 | | | |
| (9) | SG_{ijt} | 0.066*** | 0.038*** | 0.035*** | 0.028*** | 0.012*** | -0.027*** | 0.005 | 0.003 | 1 | | |
| (10) | ROA_{ijt} | 0.084*** | -0.046*** | 0.018*** | 0.075*** | -0.222*** | -0.020*** | 0.286*** | 0.192*** | 0.247*** | 1 | |
| (11) | $EShock_{ijt}$ | 0.010*** | 0.015*** | -0.019*** | 0.013*** | -0.021*** | -0.001 | 0.026*** | 0.018*** | 0.053*** | 0.089*** | 1 |

The table presents the pairwise correlations for all variables used. The firm-specific characteristics are defined as follows: AR_{ijt} is accounts receivable to total assets, AP_{ijt} is accounts payable to total assets, $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot AP_{ijt}$ is peer accounts payable to total assets, $Cash_{ijt}$ is cash and cash equivalent to total assets, $Debt_{ijt}$ is debt to total assets, $Size_{ijt}$ is size (logarithm of total assets), PPE_{ijt} is fixed assets to total assets, SG_{ijt} is sales growth, ROA_{ijt} is profitability (earnings before interest and tax to total assets) and $EShock_{ijt}$ is idiosyncratic stock returns. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Peer equity residuals.

| Panel A: Contemporaneous independent variables | | | Panel B: 1-period-lag independent variables | |
|--|----------------------|--|---|----------------------|
| Variables | (1) | | Variables | (2) |
| $Cash_{ijt}$ | -0.005 (0.005) | | $Cash_{ijt-1}$ | -0.013** (0.005) |
| $Debt_{ijt}$ | 0.013*** (0.005) | | $Debt_{ijt-1}$ | 0.011** (0.005) |
| $Size_{ijt}$ | -0.005*** (0.001) | | $Size_{ijt-1}$ | -0.008*** (0.001) |
| PPE_{ijt} | -0.012* (0.007) | | PPE_{ijt-1} | -0.007 (0.008) |
| SG_{ijt} | -0.002 (0.002) | | SG_{ijt-1} | 0.003 (0.002) |
| ROA_{ijt} | -0.009 (0.006) | | ROA_{ijt-1} | 0.003 (0.006) |
| $EShock_{ijt}$ | 0.020*** (0.001) | | $EShock_{ijt-1}$ | -0.001 (0.001) |
| Peer - firm averages | Yes | | Peer - firm averages | Yes |
| N | 63,786 | | N | 58,698 |
| Firms | 5088 | | Firms | 5088 |
| R ² | 0.216 | | R ² | 0.227 |

The table presents the estimation results of Eq. (1), which relates peer equity residuals, $P \cdot EShock_{ijt}$, to firm-specific and peer firms' average characteristics. The dependent variable, $P \cdot EShock_{ijt}$, is peer equity residuals. The firm-specific characteristics included are defined as follows: $Cash_{ijt}$ is cash and cash equivalent to total assets, $Debt_{ijt}$ is debt to total assets, $Size_{ijt}$ is size (logarithm of total assets), PPE_{ijt} is fixed assets to total assets, SG_{ijt} is sales growth, and ROA_{ijt} is profitability (earnings before interest and tax to total assets). The peer firms' average firm characteristics included are defined as follows: $P \cdot Cash_{ijt}$ is peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt}$ is peer debt to total assets, $P \cdot Size_{ijt}$ is peer size (logarithm of total assets), $P \cdot PPE_{ijt}$ is peer fixed assets to total assets, $P \cdot SG_{ijt}$ is peer sales growth, and $P \cdot ROA_{ijt}$ is peer profitability (earnings before interest and tax to total assets). The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

($P \cdot AR_{ijt}$). The goal is to examine how peer accounts receivable influence firm-specific accounts receivable. We control for other peer firm characteristics such as cash ($P \cdot Cash_{ijt-1}$), leverage ($P \cdot Debt_{ijt-1}$), size ($P \cdot Size_{ijt-1}$), tangibility ($P \cdot PPE_{ijt-1}$), sales growth ($P \cdot SG_{ijt-1}$), and return on assets ($P \cdot ROA_{ijt-1}$) as well as firm-specific characteristics, such as cash ($Cash_{ijt-1}$), debt ($Debt_{ijt-1}$), size ($Size_{ijt-1}$), tangibility (PPE_{ijt-1}), sales growth (SG_{ijt-1}), and return on assets (ROA_{ijt-1}). We then run 2SLS using peers' idiosyncratic equity shocks as instrument ($P \cdot EShock_{ijt-1}$) and the results are shown in Columns (5)–(8).

The results in Columns (1)–(4) of **Table 5** show significant positive coefficients for peer firm accounts receivable at the 1% level. Thus, consistent with **Hypothesis 1**, the results reveal that peers' trade credit policies predict the focal firm's trade credit policy. The results also imply that firms are sensitive to the trade credit policies of their peers. The magnitude of the coefficient is monotonic with

Table 5
The effect of peer firms on trade credit.

| Panel A: Main results | | | | | | | | |
|--|---------------------|----------------------|---------------------|----------------------|---------------------|----------------------|---------------------|----------------------|
| Variables | FE | | | | 2SLS | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $P \cdot AR_{ijt}$ | 0.284*** (0.025) | 0.254*** (0.024) | 0.262*** (0.027) | 0.261*** (0.025) | 0.816*** (0.126) | 0.527*** (0.121) | 0.962*** (0.192) | 0.679*** (0.180) |
| $P \cdot Cash_{ijt-1}$ | | | -0.032* (0.018) | 0.008 (0.016) | | | 0.136*** (0.049) | 0.108** (0.046) |
| $P \cdot Debt_{ijt-1}$ | | | 0.010 (0.013) | 0.006 (0.012) | | | 0.033** (0.016) | 0.020 (0.014) |
| $P \cdot Size_{ijt-1}$ | | | -0.001 (0.002) | 0.001 (0.002) | | | 0.005* (0.003) | 0.004* (0.002) |
| $P \cdot PPE_{ijt-1}$ | | | -0.029* (0.017) | 0.010 (0.016) | | | 0.086** (0.037) | 0.079** (0.035) |
| $P \cdot SG_{ijt-1}$ | | | 0.006* (0.004) | -0.006* (0.003) | | | -0.000 (0.004) | -0.010*** (0.004) |
| $P \cdot ROA_{ijt-1}$ | | | 0.031** (0.014) | 0.006 (0.014) | | | -0.011 (0.019) | -0.018 (0.018) |
| $Cash_{ijt-1}$ | | -0.147*** (0.005) | | -0.147*** (0.005) | | -0.145*** (0.005) | | -0.147*** (0.005) |
| $Debt_{ijt-1}$ | | -0.002 (0.005) | | -0.002 (0.005) | | -0.001 (0.005) | | -0.001 (0.005) |
| $Size_{ijt-1}$ | | -0.019*** (0.001) | | -0.019*** (0.001) | | -0.018*** (0.001) | | -0.018*** (0.001) |
| PPE_{ijt-1} | | -0.112*** (0.008) | | -0.113*** (0.008) | | -0.110*** (0.008) | | -0.115*** (0.008) |
| SG_{ijt-1} | | 0.014*** (0.001) | | 0.014*** (0.001) | | 0.013*** (0.001) | | 0.014*** (0.001) |
| ROA_{ijt-1} | | 0.031*** (0.005) | | 0.031*** (0.005) | | 0.028*** (0.005) | | 0.030*** (0.005) |
| $EShock_{ijt-1}$ | | | | | | 0.003*** (0.001) | | 0.003*** (0.001) |
| <i>N</i> | 63,786 | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 |
| <i>Firms</i> | 5088 | 5088 | 5088 | 5088 | 5088 | 5088 | 5088 | 5088 |
| <i>R</i> ² | 0.062 | 0.156 | 0.068 | 0.156 | 0.025 | 0.145 | 0.004 | 0.133 |
| <i>F</i> - Statistic of first stage | | | | | 24.63 | 54.78 | 22.42 | 49.40 |
| <i>F</i> <i>p</i> - value | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| Anderson LR statistic | | | | | 408.50 | 389.20 | 217.00 | 212.20 |
| Anderson LR <i>p</i> - value | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| Cragg – Donald <i>F</i> - statistic | | | | | 409.80 | 390.30 | 217.30 | 212.40 |
| Cragg – Donald <i>F</i> <i>p</i> - value | | | | | 0.008 | 0.007 | 0.004 | 0.004 |
| Cragg – Donald χ^2 statistic | | | | | 410.10 | 390.60 | 217.50 | 212.60 |
| Cragg – Donald <i>p</i> - value | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| Anderson – Rubin <i>F</i> - statistics | | | | | 44.76 | 19.50 | 28.50 | 14.96 |
| Anderson – Rubin <i>p</i> - value | | | | | 0.000 | 0.000 | 0.000 | 0.000 |
| Anderson – Rubin χ^2 statistic | | | | | 44.80 | 19.52 | 28.53 | 14.98 |
| Anderson – Rubin χ^2 <i>p</i> - value | | | | | 0.000 | 0.000 | 0.000 | 0.000 |

| Panel B: First-stage regressions | | | | | | |
|----------------------------------|--|--|---------------------|---------------------|----------------------|----------------------|
| $P \cdot EShock_{ijt-1}$ | | | 0.017*** (0.001) | 0.016*** (0.001) | 0.011*** (0.001) | 0.011*** (0.001) |
| $P \cdot Cash_{ijt-1}$ | | | | | -0.239*** (0.008) | -0.239*** (0.008) |
| $P \cdot Debt_{ijt-1}$ | | | | | -0.034*** (0.007) | -0.034*** (0.007) |
| $P \cdot Size_{ijt-1}$ | | | | | -0.008*** (0.001) | -0.008*** (0.001) |
| $P \cdot PPE_{ijt-1}$ | | | | | -0.162*** (0.008) | -0.164*** (0.008) |
| $P \cdot SG_{ijt-1}$ | | | | | 0.009*** (0.002) | 0.009*** (0.002) |
| $P \cdot ROA_{ijt-1}$ | | | | | 0.057*** (0.007) | 0.056*** (0.007) |
| $Cash_{ijt-1}$ | | | | | -0.006*** (0.002) | 0.001 (0.002) |
| $Debt_{ijt-1}$ | | | | | -0.002 | -0.002 |

(continued on next page)

Table 5 (continued)

| Panel B: First-stage regressions | | | | |
|----------------------------------|--------|----------|--------|---------|
| | | (0.002) | | (0.002) |
| $Size_{ijt-1}$ | | -0.002** | | -0.001 |
| | | (0.001) | | (0.001) |
| PPE_{ijt-1} | | -0.003 | | 0.006** |
| | | (0.003) | | (0.003) |
| SG_{ijt-1} | | 0.003*** | | 0.001 |
| | | (0.001) | | (0.000) |
| ROA_{ijt-1} | | 0.008*** | | 0.002 |
| | | (0.002) | | (0.002) |
| $EShock_{ijt-1}$ | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) |
| <i>N</i> | 58,698 | 58,698 | 58,698 | 58,698 |
| <i>Firms</i> | 5088 | 5088 | 5088 | 5088 |

The table presents the estimation results of Eq. (1), which relates accounts receivable to firm-specific and peer firms' average characteristics. The dependent variable, AR_{ijt} , is the firm's accounts receivable to total assets. The independent firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, and $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), $P \cdot EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

coefficients of 0.284, 0.254, 0.262, and 0.261 for Columns (1), (2), (3), and (4), respectively. As expected, most of the peer firm control variables in Columns (3) and (4) do not have a significant effect on the focal firm's accounts receivable. However, we find a significant negative coefficient for cash, firm size, and tangibility in Columns (2) and (4) for the firm-specific variables. The negative effect of cash and size shows that firms use trade credit to improve liquidity and that smaller firms, which generally do not have an established reputation, are more likely to extend trade credit. This finding is in line with the argument that trade credit is used as a tool to guarantee product quality and enhance marketability, especially in markets with high information asymmetry about the firm type and product quality (Long et al., 1993). We find a negative but insignificant effect for debt. Our results provide significant evidence of peer effects on the trade credit policies of firms. Both the information-based and rivalry-based theories can explain our findings to the extent that firms imitate peers of superior or similar status (Lieberman and Asaba, 2006; Adhikari and Agrawal, 2018).

Columns (5)–(8) of Table 5 provide the results for the 2SLS estimation of peer effects on trade credit policies. Similar to the FE estimation, the dependent variable is the firm's accounts receivable, and the main independent variable is the peer firms' average accounts receivable. As usual, we control for both firm-specific and peer firm characteristics. Panel B of Table 5 shows the first-stage regressions of the 2SLS model, in which the dependent variable is peer accounts receivable and the instrument is the lagged peers' idiosyncratic return shocks ($P \cdot EShock_{ijt-1}$). As expected, the results reveal that the variable predicts peers' accounts receivable significantly and positively at the 1% level, even after controlling for several other important determinants of trade credit. In the second stage of the 2SLS model, we find that the coefficient of peer firms' accounts receivable is significantly positive in all the models at the 1% level. The magnitude of the peer effect is larger than using the FE with coefficient estimates of 0.816, 0.527, 0.962, and 0.679 in Columns (5), (6), (7), and (8), respectively. This effect is not only statistically significant but also economically substantial.

Overall, consistent with our hypothesis, we find evidence suggesting that there is significant peer influence on a given firm's trade credit policy.

5.2. Product market competition and peer effects

Next, we test the hypothesis that when product market competition is high, firms are more likely to be active in responding to the trade credit policies of their peers (Hypothesis 2). Lieberman and Asaba (2006) argue that imitation increases in competitive markets in line with the rivalry-based theory, because firms attempt to maintain competitive parity. The increased intensity of competition over the last 3 decades (He and Wintoki, 2016) brings into sharp focus the importance of trade credit in managing product market competition. Unlike capital structure decisions, in which managers tend to be inert in more competitive industries (Beniers and Dur, 2003), trade credit enhances a firm's competitive positioning with direct influence on profitability. In a less competitive environment, product differentiation is more straightforward, and thus, there is less need to imitate other firms' trade credit policies to signal a firm's product quality to customers (Adhikari and Agrawal, 2018). Moreover, product differentiation is difficult in a more competitive market with many sellers and similar products. The ability to exercise market power in a competitive industry decreases the uncertainty about the firm's future performance (Gaspar and Massa, 2006; Pástor and Pietro, 2003). Therefore, consistent with the rivalry-based theory, replicating the trade credit policies of peer firms should be more pronounced in more competitive industries

Table 6
Product market competition and peer effects on trade credit.

| Variables | HHI (assets) | | HHI (sales) | | Lerner index | |
|--------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | Low | High | Low | High | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $P \cdot AR_{ijt}$ | 0.915*** (0.216) | 0.548** (0.269) | 0.819*** (0.256) | 0.541** (0.247) | 0.838*** (0.272) | 0.655** (0.287) |
| First-stage regressions | | | | | | |
| $P \cdot EShock_{ijt-1}$ | 0.017*** (0.001) | 0.009*** (0.001) | 0.015*** (0.001) | 0.010*** (0.001) | 0.012*** (0.001) | 0.010*** (0.001) |
| Firm - specific controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Peer - firm averages | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 28,494 | 28,699 | 27,911 | 28,672 | 28,487 | 28,394 |
| Firms | 3125 | 3069 | 3066 | 3146 | 3924 | 3318 |
| R ² | 0.143 | 0.093 | 0.153 | 0.095 | 0.078 | 0.183 |
| F - statistic | 138.400 | 64.260 | 144.800 | 74.790 | 80.270 | 56.000 |
| KP LM statistic | 128.200 | 62.620 | 132.400 | 72.640 | 75.670 | 54.840 |
| KP LM p - value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

The table presents the estimation results of Eq. (1), which relates accounts receivable to firm-specific and peer firms' average characteristics. The dependent variable, AR_{ijt} , is the firm's accounts receivable to total assets. The independent firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), and $P \cdot EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firm's average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample is partitioned into high (low) market competition if the firm is above (below) the median Herfindahl–Hirschman index (HHI index) calculated based on total assets (HHI (assets)) and sales (HHI (sales)). Columns (1)–(6) present the results for the samples partitioned based on HHI (assets), and Columns (7)–(12) present the results for the samples partitioned based on HHI (sales). The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

than in less competitive industries.

Table 6 presents the results estimating Eq. (1) on sub-samples of high and low market competition. We examine the effects of market competition on peer firm influence on trade credit policies using three proxies of product market competition based on the Herfindahl–Hirschman index (assets), Herfindahl–Hirschman index (sales), and the Lerner index (Lerner, 1934). We partition the sample into a high (low) market competition if the firm is below (above) the median Herfindahl–Hirschman index (HHI) calculated based on total assets (HHI (assets)) and sales (HHI (sales)). A low Lerner index also implies high competition (i.e., low monopoly power) and a high Lerner index represents low competition. Columns (1) and (2) present the results for the samples that are partitioned based on HHI (assets), Columns (3) and (4) present the results for the samples that are partitioned based on HHI (sales), and Columns (5) and (6) presents the results for the Lerner index. The dependent variable is the firm's accounts receivable, and the independent variable is the peer average accounts receivable. We run a 2SLS model using the peer firm idiosyncratic equity shocks ($P \cdot EShock_{ijt-1}$) as the instrument with the same control variables as in previous models for these estimations. For brevity, we do not report the results for all the variables used in the models.

We observe that all the coefficients of peer effects in Table 6 are significant and of the expected sign. The coefficient of peer accounts receivable is positive and significant at the 1% level in Columns (1), (3), and (5) for high competition. Even though we observe positive coefficients for peer accounts receivable for both low and high competition sub-samples, the magnitude of the effects is larger for high competition (Columns (1), (3), and (5)) than for low competition (Columns (2), (4), and (6)). Thus, the coefficients of peer effects are larger (at least 66% larger) for firms in high product market competition (low HHI and low Lerner index) relative to low product market competition (high HHI and high Lerner index). This result is consistent with the proposition that trade credit is used to compete in less concentrated industries. According to the rivalry-based theory of mimicking behavior, firms imitate others to maintain competitive parity or limit rivalry (Lieberman and Asaba, 2006). Trade credit also serves as a significant tool to enhance competitive positioning in the product market through price competition and assurance of product quality (Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1996; Petersen and Rajan, 1997). In essence, trade credit as a competitive device in the product market improves supplier-customer relations (Ng et al., 1999; Cuat, 2007), and enhances the firm's sales and profitability (Martínez-Sola et al., 2013; Box et al., 2018).

Overall, our results are consistent with the rivalry theory of imitation and suggest that peer effects increase with product market competition. Intense competition in the product market forces managers to adapt their corporate decisions in response to the actions of their peers. Moreover, whereas firms use accounts payable to manage financial market imperfections, accounts receivable enables

Table 7
Information environment and peer effects on trade credit.

| Variables | Probability of informed trading (PIN) | | Standard deviation of analyst earnings estimates (ASTdev) | | Number of analysts followings (Numest) | |
|--------------------------|---------------------------------------|---------------------|---|---------------------|--|---------------------|
| | Low | High | Low | High | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $P \cdot AR_{ijt}$ | 0.339 (0.247) | 0.932*** (0.307) | 0.693** (0.290) | 0.755*** (0.272) | 0.720*** (0.228) | 0.624** (0.274) |
| First-stage regressions | | | | | | |
| $P \cdot EShock_{ijt-1}$ | 0.011*** (0.001) | 0.010*** (0.001) | 0.010*** (0.001) | 0.011*** (0.001) | 0.013*** (0.001) | 0.011*** (0.001) |
| Firm - specific controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Peer - firm averages | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 28,039 | 28,656 | 28,048 | 28,435 | 28,747 | 27,251 |
| Firms | 2721 | 2550 | 2660 | 2485 | 2489 | 2580 |
| R ² | 0.167 | 0.045 | 0.135 | 0.104 | 0.108 | 0.154 |
| F - statistic | 77.02 | 54.98 | 52.97 | 79.77 | 103.70 | 73.20 |
| KP LM statistic | 72.00 | 53.27 | 51.27 | 74.81 | 97.04 | 66.22 |
| KP LM p - value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

The table presents estimation results of Eq. (1), which relates accounts receivable to firm-specific and peer firms' average characteristics based on the level of information environment (probability of informed trading, standard deviation of analyst earnings estimates, and number of analyst followings). The dependent variable, AR_{ijt} , is the firm's accounts receivable to total assets. The independent firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), and $P \cdot EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firm's average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample is partitioned into low and high sub-samples based on whether the firm is below or above the median of probability of informed trading (Columns (1)–(2)), standard deviation of analyst earnings estimates (Columns (3)–(4)), and number of analyst followings (Columns (5)–(6)). The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

firms to manage growth via the product market (Ferrando and Mulier, 2013). However, unlike capital structure decisions, in which managers tend to be inert in more competitive industries (Beniers and Dur, 2003), our findings highlight the importance of trade credit owing to its direct impact on sales and profitability.

5.3. Information environment and peer effects

Table 7 presents the results for sub-samples of firms classified as operating in environments with more and less industry information (Hypothesis 3). Information theory posits that imitation increases in an environment with high information asymmetry (Lieberman and Asaba, 2006; Adhikari and Agrawal, 2018). In other words, in such environments, firms are more likely to mimic their peers to signal information about their quality or to establish a reputation. Our first proxy of the information environment is the probability of informed trading (PIN) measure of Brown and Hillegeist (2007), where a larger PIN reflects a high information environment. The second proxy is the standard deviation of analysts' earnings estimates (ASTdev), with high deviation indicating high uncertainty in the market. Finally, we measure information asymmetry using the number of analysts' followings (Jegadeesh et al., 2004; Adhikari, 2016; Adhikari and Agrawal, 2018), with lower followings implying a poorer information environment. In line with our hypothesis and consistent with the information theory of imitation, we expect an increase in peer effects when there is high information asymmetry. Thus, we partition the results based on the three proxies for industry information environment and estimate a 2SLS model similar to Table 5.

Table 7 reports the results of the 2SLS estimation using the peer firm idiosyncratic equity shocks ($P \cdot EShock_{ijt-1}$). As usual, our dependent variable is the firm's accounts receivable, and the main independent variable is the average industry accounts receivable for peer firms while controlling for peer firms' and firm-specific characteristics. Columns (1) and (2) present the results for low PIN and high PIN, respectively, where the coefficient of ($P \cdot AR_{ijt}$) is positive and significant for the high PIN sub-sample. This result indicates that peer influence increases in a poorer information environment. Our results are similar to those in Columns (3) and (4), with a larger coefficient for high (ASTdev) and low (Numest). These results are both in line with the information theory, that imitation increases in a poorer information environment.

Overall, these results shed light on the importance of the information environment for peer effects. This evidence is in line with Lieberman and Asaba (2006), who argue that peer effects increase in the presence of higher information uncertainty. In broader

Table 8
Leaders and followers: Who mimics the other?

| Panel A: | Market capitalization | | | Liquidity | | | Profitability | | | | | |
|---------------------------------|-----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | Low | High | | Low | High | | Low | High | | | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\Delta P \cdot AR_{it}^{Low}$ | 0.625*** (0.171) | 0.229 (0.170) | 0.453** (0.196) | 0.622*** (0.133) | 0.825*** (0.170) | 0.204* (0.122) | 0.277** (0.131) | 0.456** (0.203) | 0.473*** (0.178) | 0.485*** (0.187) | 0.601*** (0.168) | 0.535*** (0.180) |
| $\Delta P \cdot AR_{it}^{High}$ | | | | | | | | | | | | |
| First-stage regressions | | | | | | | | | | | | |
| $P \cdot EShock_{it-1}^{Low}$ | 0.019*** (0.002) | 0.020*** (0.001) | 0.009*** (0.002) | 0.017*** (0.001) | 0.015*** (0.001) | 0.017*** (0.002) | 0.020*** (0.002) | 0.013*** (0.002) | 0.013*** (0.001) | 0.014*** (0.001) | 0.010*** (0.001) | 0.013*** (0.001) |
| $P \cdot EShock_{it-1}^{High}$ | | | | | | | | | | | | |
| Peer - firm averages | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm - specific factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 25,502 | 26,093 | 21,395 | 27,129 | 26,453 | 24,756 | 25,822 | 25,541 | 25,791 | 25,376 | 25,427 | 26,149 |
| Firms | 3030 | 3091 | 2122 | 2551 | 3341 | 3246 | 3474 | 3460 | 3931 | 3897 | 3256 | 3263 |
| R ² | 0.065 | 0.089 | 0.034 | 0.103 | 0.031 | 0.092 | 0.096 | 0.090 | 0.074 | 0.075 | 0.079 | 0.106 |
| F - statistic | 57.73 | 282 | 18.08 | 216.3 | 123.9 | 67.96 | 133.9 | 56.61 | 106.3 | 106.3 | 76.85 | 84.87 |
| KP LM statistic | 49.95 | 252.1 | 18.24 | 190.1 | 111.8 | 59.38 | 141.3 | 55.58 | 106.4 | 99.24 | 74.11 | 80.19 |
| KP LM p - value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Panel B: | Tangibility | | | Age | | | Leverage | | | | | |
| Variables | Low | High | | Young | Mature | | Low | High | | Low | High | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\Delta P \cdot AR_{it}^{Low}$ | 0.506*** (0.140) | 0.801*** (0.296) | 0.326** (0.144) | 0.714*** (0.190) | 0.439*** (0.128) | 0.249 (0.185) | 0.425*** (0.107) | 0.478*** (0.139) | 0.572*** (0.222) | 0.474*** (0.148) | 0.328** (0.161) | 0.508*** (0.147) |
| $\Delta P \cdot AR_{it}^{High}$ | | | | | | | | | | | | |
| First-stage regressions | | | | | | | | | | | | |
| $P \cdot EShock_{it-1}^{Low}$ | 0.024*** (0.002) | 0.010*** (0.001) | 0.010*** (0.002) | 0.011*** (0.001) | 0.019*** (0.002) | 0.015*** (0.001) | 0.016*** (0.002) | 0.017*** (0.001) | 0.013*** (0.002) | 0.017*** (0.002) | 0.013*** (0.002) | 0.016*** (0.001) |
| $P \cdot EShock_{it-1}^{High}$ | | | | | | | | | | | | |
| Peer - firm averages | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm - specific factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 25,719 | 24,237 | 21,002 | 26,476 | 25,921 | 25,982 | 26,330 | 26,939 | 25,899 | 26,132 | 24,766 | 26,331 |
| Firms | 3119 | 3051 | 2611 | 2925 | 3867 | 3865 | 2321 | 2327 | 3302 | 3332 | 3348 | 3442 |

(continued on next page)

Table 8 (continued)

| Variables | Tangibility | | | Age | | | Leverage | | | | | |
|-----------------|-------------|-------|-------|-------|-------|--------|----------|-------|-------|-------|-------|-------|
| | Low | | High | Young | | Mature | Low | | High | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| R^2 | 0.094 | 0.048 | 0.074 | 0.068 | 0.095 | 0.103 | 0.079 | 0.095 | 0.081 | 0.091 | 0.085 | 0.085 |
| F - statistic | 136.4 | 49.94 | 21.82 | 92.79 | 145.6 | 100.1 | 107.7 | 161.9 | 50.47 | 90.35 | 67.32 | 129.3 |
| KP LM statistic | 121.8 | 49.41 | 20.14 | 87.07 | 129.4 | 102.6 | 96.81 | 133.8 | 49.20 | 86.13 | 62.04 | 115.1 |
| KP LM p - value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

The table presents the estimation results of Eq. (1), which relates change in accounts receivable to firm-specific and peer firms' average characteristics. The dependent variable, ΔAR_{ijt} , is the firm's change in accounts receivable to total assets. The independent firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $\Delta P \cdot AR_{ijt}$ is the change in peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), and $P \cdot EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firm's average characteristics are calculated as the average of all firms within an industry-year excluding the t^{th} observations. Industries are defined by the three-digit SIC code. In Panel A, the sample is partitioned into low and high sub-samples based on whether the firm is below or above the median of industrial market capitalization (Columns (1)–(4)), liquidity (Columns (5)–(8)), and profitability (Columns (9)–(12)). The sample in Panel B is partitioned into low and high sub-samples based on whether the firm is below or above the median of tangibility (Columns (1)–(4)), age (Columns (5)–(8)), and leverage (Columns (9)–(12)). The sample consists of listed non-financial and non-utility firms in the United States drawn from Compustat over the period 1977–2016. All variables used are defined in Appendix A, and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

terms, our findings illuminate the evidence on the impact of peer information disclosures on a firm's decisions. Shroff et al. (2013) and Shroff et al. (2017) assert that a firm's information disclosures have significant economic consequences for its peers, since firms in the same industry are affected by similar economic shocks. Therefore, concerning trade credit, firms are sensitive to the industry information environment, mainly because the externalities associated with information disclosures reduce information asymmetry in the industry (Myers, 1984; Healy and Palepu, 2001; Lambert et al., 2012).

5.4. Heterogeneity in peer effects

This subsection investigates whether peer effects are homogeneous or heterogeneous conditional on whether or not the firms are leaders/followers (Hypothesis 4). We examine the heterogeneity in the peer effects to explain why firms mimic the trade credit policies of their peers. We follow Adhikari and Agrawal (2018) and define firms as leaders/followers using such variables as market capitalization, liquidity, profitability, tangibility, age, and leverage. Firms are classified as leaders (followers) if each of the measures is above (below) the median value. Generally, mimicking behavior can range from the interaction between financial structure and product market competition, because of price competition (Bolton and Scharfstein, 1990) and loss of market share (Chevalier and Scharfstein, 1996). Consistent with Scharfstein and Stein (1990) and Petersen and Rajan (1997), firms may replicate the trade credit policies of their peers to influence perceived relative quality in the product market.

In Table 8, we examine whether some firms within the industry are more or less sensitive to the trade credit policies of their peers. Follower firms are likely to adapt their trade credit policies to reflect the policies of their leader peers. For follower firms, replicating the trade credit policies of their peers is a source of quality information to capture a share of the market. However, it can be argued that leaders may also adopt the trade credit policies of their follower peers to consolidate their market share in the product market (Brander and Lewis, 1986; Bolton and Scharfstein, 1990; Sharapov and Ross, 2019), a phenomenon that is in line with the feedback motive of the information theory Lieberman and Asaba (2006). Thus, to elucidate our understanding of the motivation of peer effects, it is necessary to explore whether peer effects are driven by a leader–follower model in which followers respond to the trade credit policies of leaders and vice versa.

Panel A of Table 8 presents the 2SLS regression results using market capitalization, liquidity, and profitability to define leader firms. Panel B splits the sample into leaders and followers based on tangibility, firm age, and leverage. The coefficients of changes in peers' accounts receivable are significantly positive in all columns except Column (2). Our findings are consistent with the argument that follower firms (low market share, less liquid, and less profitable) are more responsive to the trade credit policies of their leader peers. Leary and Roberts (2014) and Francis et al. (2016) find similar results for financing decisions. More tellingly, however, we find that the opposite is also true. Thus, leader firms (high market share, more liquid, and more profitable) also respond to the trade credit policies of their follower peers. The results are similar when leader firms are defined using tangibility, firm age, and leverage.

The implications of these findings are consistent with the learning motive (Scharfstein and Stein, 1990; Leary and Roberts, 2014) of the information theory by which followers learn from leaders. The findings that leaders also learn from followers are a reflection of the feedback theory of predation (e.g., Brander and Lewis, 1986; Bolton and Scharfstein, 1990), by which leaders mimic their followers to defend their market lead, to undercut and force the followers out of business. This evidence reinforces the notion that trade credit serves as a significant competitive tool in the product market, which influences market leaders to respond even to the trade credit policies of their follower peers. The results further show that the trade-offs between the benefits and costs of trade credit do not undermine peer effects. To the extent that firms perceive that there are greater benefits than costs of investing in accounts receivable (Giannetti et al., 2011; Aktas et al., 2012; Martínez-Sola et al., 2013; Hill et al., 2015), they are likely to respond to the trade credit policies of their peers.

5.5. Does mimicking matter?

To understand the implications of mimicking trade credit, we estimate the following Tobin's q model⁹:

$$q_{ijt} = \gamma_0 + \gamma_1 \widehat{AR/TA}_{-ijt-1} + \gamma_2 \widehat{AR/TA}_{-ijt-1}^2 + \Gamma \mathbf{Z}_{ijt-1} + \mu_t + \xi_{ijt} \quad (5)$$

where q_{ijt} is the value of firm i in industry j at time t , and γ_0 is a constant. γ_1 , γ_2 , and θ are the vectors of coefficients to be estimated. $\widehat{AR/TA}_{-ijt-1}$ and $\widehat{AR/TA}_{-ijt-1}^2$ are the lagged predicted peer effects and squared term of the lagged predicted peer effects, respectively. \mathbf{Z}_{ijt-1} is a vector of lagged cash (*Cash*), debt (*Debt*), firm-size (*Size*), property, plant and equipment (*PPE*), and sales growth (*Sales Growth*). μ_t are the year-fixed effects. Finally, ξ_{ijt} is the error term. We estimate Eq. (5) using 2SLS. As discussed earlier in Section 4.2, we use peer firms' idiosyncratic equity idiosyncratic return shock as an instrument for the endogenous peer effects ($\widehat{AR/TA}_{-ijt-1}$). In the first stage, we generate the predicted value, $\widehat{AR/TA}$, from running a linear regression relating trade credit to the instrument and control variables. In the second stage, we then use the predicted value of trade credit in Eq. (5). To examine asymmetry in the firm value–trade credit nexus, we sub-divide the sample into two groups in each year based on whether a firm is ranked in the

⁹ Several studies include a quadratic term, as we have done, to examine non-linearities in corporate decisions (see Banos-Caballero et al., 2014; Nason and Patel, 2016; Ben-Nasr, 2016; Park et al., 2017; Gao et al., 2018). For example, Nason and Patel (2016) include a squared term of cash holdings to examine the non-linear effects of cash holdings on firm value. Similarly, Gao et al. (2018) use a squared term and find a non-monotonic hump-shaped relationship between cash and interest rates. Within the trade credit literature, Martínez-Sola et al. (2013) find a non-linear effect of trade credit on firm value.

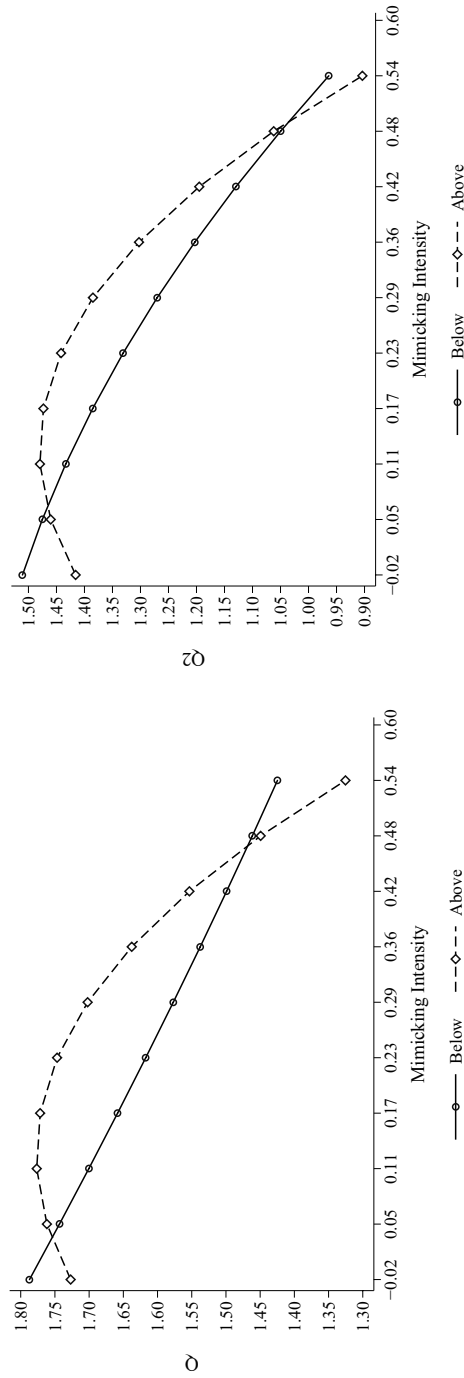


Fig. 1. The implications of following peer firms' trade credit policies. The figure plots the marginal effects of following peer firms' trade credit calculated from estimating Eq. (5) using 2SLS. Firms are sub-divided into two groups in each year based on whether a firm is ranked in the lower quartile of trade credit (Below) and upper quartile of trade credit (Above). The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles.

lower–Below (upper–Above) quartile of trade credit. Fig. 1 plots the marginal effects of peer effects calculated from estimating Eq. (5) for the two sub-samples.

Fig. 1 reveals interesting insights into the effects of mimicking on firm value. The plots show that the benefits of mimicking are higher for firms in the lower quartile than for those in the upper quartile.¹⁰ These findings corroborate Martínez-Sola et al. (2013) and Hill et al. (2015), who show the diminishing returns to offering higher levels of trade credit. Our findings extend this line of inquiry by showing that mimicking trade credit is similarly associated with diminishing benefits and that these benefits diminish at a faster rate for firms that mimic and end up straying above the optimal point. Thus, mimicking may benefit firms in reducing the search costs for information required for them to optimize their trade credit policies. However, mimicking can also be detrimental, as it could result in the firm paying more attention to its peers and in the process neglecting its information or competitive advantages (Fairhurst and Nam, 2020). As depicted in Fig. 1, the latter costs of mimicking appear to apply mostly to mimicking firms with very high trade credit. Based on these results, we conclude that mimicking is beneficial if it reduces search costs and moves the firm closer to optimal trade credit policies. However, beyond this level, following peers with less regard to the focal firm's fundamentals might lead to less optimal trade credit policies.

6. Robustness checks

We implement several robustness tests. First, we examine whether peer effects vary across different industry structures. Table 9 shows the FE and 2SLS regression output for each industry structure. Here, we partition the sample firms into non-manufacturing (Columns (1) and (2)), manufacturing (Columns (3) and (4)), technology (Columns (5) and (6)), durables (Columns (7) and (8)), and non-durables (Columns (9) and (10)). These sub-sample analyses are premised on the notion that firms in different industry structures adopt different strategies and respond to their peers differently. Firms producing standardized products give less trade credit (see, e.g., Guariglia and Mateut, 2013; Giannetti et al., 2011). Thus, for firms operating in technology industries, in which reputation is paramount and it takes a considerable amount of time to develop software, trade credit is essential to establish the quality of the product. We expect this effect to also exist in manufacturing, but not non-durable industries.

Our results show that the coefficient of peer accounts receivable is significantly positive at the 1% level for the manufacturing and technology sub-samples (at 5% for 2SLS). This evidence is consistent with the hypothesis that peer effects on trade credit are more pronounced across firms operating in the manufacturing and technology sectors. There is some evidence of peer effects on trade credit in the non-manufacturing and durables sectors. However, we find no evidence of peer effects in the non-durables sector. This result supports the proposition that trade credit is used to alleviate imperfections in product markets, as it allows customers to try the product before making a payment (Antras and Foley, 2015; Lee and Stowe, 1993; Long et al., 1993). Durable goods can be preserved for a long time, and customers can establish their quality over a long period. Hence, they are more willing to demand trade credit for durable goods than for non-durables, which are purchased for immediate consumption.

The results in Table 10 test the peer effects on trade credit using alternative measures of trade credit. Panel A provides the results for accounts receivable measured as total receivables to total assets (TR/TA), accounts receivable to net assets (AR/NA), days of sales outstanding (DSO), and change in accounts receivable to sales (Δ AR/Sales). In all the estimations, the coefficient of accounts receivable is positive and statistically significant at the 1% level. These results indicate that a specific measure of trade credit does not drive our earlier findings. In Panel B, we examine the peer effects on accounts payable using both FE and 2SLS estimations, as defined in Table 5. Again, our results show significant positive peer effects on accounts payable. Overall, the results are robust to alternative proxies for trade credit.

As additional robustness tests, we use alternative instruments for the 2SLS estimation and re-run the baseline models. We follow Leary and Roberts (2014) directly and use the average peer idiosyncratic return shock after estimating their augmented market model. Peer groups and industry are defined by the three-digit SIC code and we follow a similar approach to that explained in Section 4.2 to estimate the expected and idiosyncratic returns. Consistent with our earlier results, in the untabulated results, we find that the coefficient of peer accounts receivable is significantly positive in all the models. Thus, our results and findings remain robust to the alternative instruments for the 2SLS estimation, showing that the choice of estimation instruments does not merely drive the earlier results.

We also classify industry using the one-digit SIC, two-digit SIC, Fama and French 48 industry groups (Fama and French, 1997), and Fama and French 10 industry groups. This approach is to assure that our results are not necessarily driven by how the industry is classified. This estimation reproduces merely the base model with the firm's accounts receivable as the dependent variable and peer firm accounts receivable as the independent variable. The control variables are similar to those of Table 5. The results are not tabulated but we find that there is a positive relationship between peer accounts receivable and the firm's accounts receivable in all the models for FE and 2SLS. Thus, regardless of the industry classification, our earlier results still hold. Firms are sensitive to the trade credit policies of their industry peers. Our results remain robust to these alternative industry classifications.

Finally, we re-run our baseline models and control for the effects of macroeconomic variables and monetary policy. For example, Mateut et al. (2006) find that monetary policy tightening reduces bank lending and increases the demand for trade credit. The recent financial crises resulted in both credit-rationed firms and self-rationed firms resorting to alternative external financing, including trade credit (Casey and O'Toole, 2014). Thus, a contraction in the economy adversely restricts bank lending owing to increased

¹⁰ Appendix B presents the estimation results of Eq. (5), showing significant variations in the effect of mimicking on firm value conditional on being in the lower or upper quartile.

Table 9
Robustness: Sub-samples.

| Variables | Non-manufacturing | | Manufacturing | | Technology | | Durables | | Non-durables | |
|--------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|-------------------|---------------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $P \cdot AR_{ijt}$ | 0.270*** (0.037) | 0.251 (0.469) | 0.182*** (0.032) | 0.789*** (0.173) | 0.232*** (0.084) | 0.825** (0.321) | 0.094* (0.050) | 0.893*** (0.271) | 0.053 (0.049) | 1.466 (2.267) |
| First-stage regressions | | | | | | | | | | |
| $P \cdot EShock_{ijt-1}$ | | 0.006*** (0.001) | | 0.017*** (0.001) | | 0.023*** (0.001) | | 0.017*** (0.002) | | 0.002 (0.002) |
| Estimation method | FE | 2SLS | FE | 2SLS | FE | 2SLS | FE | 2SLS | FE | 2SLS |
| Peer - firm averages | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm - specific factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 22,748 | 22,748 | 35,950 | 35,950 | 14,804 | 14,804 | 11,817 | 11,817 | 8593 | 8593 |
| Firms | 2194 | 2194 | 2894 | 2894 | 1235 | 1235 | 926 | 926 | 672 | 672 |
| R ² | 0.117 | 0.117 | 0.190 | 0.155 | 0.235 | 0.226 | 0.162 | 0.091 | 0.177 | -0.161 |
| F - statistic | | 18.30 | | 211.8 | | 428.1 | | 95.48 | | 1.406 |
| KP LM statistic | | 17.68 | | 194.3 | | 261 | | 80.95 | | 1.409 |
| KP LM p - value | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.235 |

The table presents the estimation results of Eq. (1), which relates accounts receivable to firm-specific and peer firms' average characteristics. The dependent variable, AR_{ijt} , is the firm's accounts receivable to total assets. The independent firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample is partitioned into industry sectors: non-manufacturing (Columns (1)–(2)), manufacturing (Columns (3)–(4)), technology (Columns (5)–(6)), durables (Columns (7)–(8)), and non-durables (Columns (9)–(10)). The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A, and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

lending costs and may encourage suppliers to meet customers' demand for trade credit. We control for GDP growth rate, domestic credit to private sector by banks as a % of GDP, public debt, real interest rates, risk premium, lending rates, and growth in money supply to capture the effects of the macroeconomic and monetary policy dynamics. Our results still hold, that is, there remains a positive and significant impact of peer accounts receivable on the focal firm's accounts receivable. The results are not tabulated for brevity. Peer influence on trade credit exists beyond the traditional explanations about firm level and the impact of macroeconomics and monetary policy changes.

7. Conclusion

Prior literature extensively documents peer effects on corporate financial decisions, such as capital structure, dividend policy, and cash holdings. However, peer effects on trade credit have largely been ignored. Given the significant economic impact of trade credit, we examine whether and how peer firms influence trade credit in the United States over the past 5 decades. Given that firms use trade credit as a tool to gain competitive parity or to limit rivalry in the product market, we test the influence of industry competition on the impact of peer trade credit policy on firms. We also examine heterogeneity in peer effects to establish whether peer effects are a symptom of followers mimicking leaders, or whether the feedback theory holds in that successful firms are also sensitive to the actions of their less successful peers.

We find that average peer trade credit is positively related to a firm's trade credit. In other words, firms increase their accounts receivable in response to an increase in the accounts receivable of their industry peers. The results are consistent with the information-based theories of peer effects, in which firms mimic the decisions of industry peers that are perceived to possess superior information about the market. Moreover, peer effects are more significant for firms that face higher product market competition and operate in a better information environment. While we find evidence in support of the learning motive, that less successful firms are responsive to the trade credit policy of their more successful firms, we also find that more successful firms are sensitive to the trade credit policies of their less successful peers. This evidence highlights the importance of trade credit as a competitive device to gain and maintain market share, which ultimately translates into improving sales and profitability. Our results are robust to alternative estimation techniques, several alternative measures of accounts receivable, and a host of other tests.

Overall, our results support the proposition that a firm's trade credit policies can be influenced by its peer firms' trade credit policies. Thus, as with other corporate policies, peer effects also exist in trade credit. We note, however, that our sample of firms is limited to publicly listed firms. As such, our findings might not be generalizable to an important segment of the market, namely, unlisted small and medium-sized enterprises. We leave this subject for future investigation. Moreover, our sample is limited to firms

Table 10
Robustness: Alternative measures of trade credit.

| Panel A: Accounts receivable | | | | | | | | |
|--------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | TR/TA | | AR/NA | | DSO | | ΔAR/Sales | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $P \cdot AR_{ijt}$ | 0.258*** (0.024) | 0.859*** (0.230) | 0.269*** (0.026) | 0.549*** (0.191) | 0.250*** (0.016) | 0.560*** (0.191) | 0.478*** (0.020) | 0.527*** (0.123) |
| First-stage regressions | | | | | | | | |
| $P \cdot EShock_{ijt-1}$ | | 0.009*** (0.001) | | 0.012*** (0.001) | | 0.153*** (0.013) | | 0.017*** (0.001) |
| <i>Estimation method</i> | FE | 2SLS | FE | 2SLS | FE | 2SLS | FE | 2SLS |
| <i>Peer - firm averages</i> | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>Firm - specific factors</i> | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>N</i> | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,584 | 58,584 |
| <i>Firms</i> | 5088 | 5088 | 5088 | 5088 | 5088 | 5088 | 5082 | 5082 |
| <i>R²</i> | 0.150 | 0.102 | 0.112 | 0.103 | 0.034 | 0.024 | 0.097 | 0.100 |
| <i>F - statistic</i> | | 90.14 | | 130.3 | | 147.6 | | 481.7 |
| <i>KP LM statistic</i> | | 87.43 | | 124.3 | | 140.9 | | 401.7 |
| <i>KP LM p - value</i> | | 0.000 | | 0.000 | | 0.000 | | 0.000 |
| Panel B: Accounts payable | | | | | | | | |
| | AP/TA | | AP/NA | | DPA | | ΔAP/Sales | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $P \cdot AP_{ijt}$ | 0.195*** (0.029) | 0.810*** (0.300) | 0.195*** (0.028) | 0.698** (0.315) | 0.247*** (0.026) | 1.235** (0.531) | 0.353*** (0.024) | 0.452** (0.226) |
| First-stage regressions | | | | | | | | |
| $P \cdot EShock_{ijt-1}$ | | 0.005*** (0.001) | | 0.005*** (0.001) | | 0.032*** (0.007) | | 0.006*** (0.000) |
| <i>Estimation method</i> | FE | 2SLS | FE | 2SLS | FE | 2SLS | FE | 2SLS |
| <i>Peer - firm averages</i> | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>Firm - specific factors</i> | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>N</i> | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,698 | 58,584 | 58,584 |
| <i>Firms</i> | 5088 | 5088 | 5088 | 5088 | 5088 | 5088 | 5082 | 5082 |
| <i>R²</i> | 0.078 | 0.029 | 0.067 | 0.036 | 0.027 | -0.077 | 0.055 | 0.056 |
| <i>F - statistic</i> | | 67.61 | | 55.81 | | 21.90 | | 169.7 |
| <i>KP LM statistic</i> | | 67.78 | | 56.31 | | 22.17 | | 161.8 |
| <i>KP LM p - value</i> | | 0.000 | | 0.000 | | 0.000 | | 0.000 |

The table presents the estimation results of Eq. (1), which relates trade credit to firm-specific and peer firms' average characteristics. TR/TA_{ijt} is total receivables to total assets. AR/NA_{ijt} is accounts receivable to net assets and net assets is total assets less cash and cash equivalent. DSO_{ijt} is days' sales outstanding. AP/TA_{ijt} is accounts payable to total assets. AP/NA_{ijt} is accounts payable to net assets. DPA_{ijt} is days in accounts payable outstanding. The firm-specific characteristics are defined as follows: AR_{ijt} is accounts receivable to total assets, $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, ROA_{ijt-1} is lagged profitability (earnings before interest and tax to total assets), and $EShock_{ijt}$ is the lagged idiosyncratic stock returns. The peer firms' average firm characteristics are defined as follows: $P \cdot AR_{ijt}$ is peer accounts receivable to total assets, $P \cdot Cash_{ijt-1}$ is lagged peer cash and cash equivalent to total assets, $P \cdot Debt_{ijt-1}$ is lagged peer debt to total assets, $P \cdot Size_{ijt-1}$ is lagged peer size (logarithm of total assets), $P \cdot PPE_{ijt-1}$ is lagged peer fixed assets to total assets, $P \cdot SG_{ijt-1}$ is lagged peer sales growth, $P \cdot ROA_{ijt-1}$ is lagged peer profitability (earnings before interest and tax to total assets), and $P \cdot EShock_{ijt}$ is the lagged peer idiosyncratic stock returns. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC code. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

in the United States, but we know that US firms compete with firms from other countries. Accordingly, future research could also explore mimicking of trade credit policies across countries.

Declaration of Competing Interest

None

Appendix A: Variable definitions

The table lists the definitions of all variables used and the account items obtained from the Compustat databases.

| Variable | Definition |
|------------------|--|
| AR_{ijt} | Accounts receivable (<i>RECTR</i>) to total assets (<i>AT</i>). |
| $Cash_{ijt}$ | Cash and cash equivalent (<i>CHE</i>) to total assets. |
| $Debt_{ijt}$ | Debt (<i>DLC</i> + <i>DLTT</i>) to total assets. |
| $Size_{ijt}$ | Log of total assets. |
| PPE_{ijt} | Fixed assets (<i>PPENT</i>) to total assets. |
| SG_{ijt} | Change in sales (<i>SALE</i>) to lagged sales ($(Sales_{ijt} - Sales_{ijt-1})/Sales_{ijt-1}$). |
| ROA_{ijt} | Earnings before interest and tax (<i>EBIT</i>) to total assets. |
| $EShock_{ijt}$ | Annual idiosyncratic return calculated by taking the geometric average of the monthly idiosyncratic from Eq. (4). |
| TR/TA_{ijt} | Total receivables (<i>RECT</i>) to total assets. |
| NTC/TA_{ijt} | Net trade credit (accounts receivable less accounts payable) to total assets. |
| AR/NA_{ijt} | Accounts receivable to net assets (<i>AT</i> - <i>CHE</i>). Net assets are total assets less cash and cash equivalent. |
| DSO_{ijt} | Days' sales outstanding. |
| AP/TA_{ijt} | Accounts payable (<i>AP</i>) to total assets. |
| AP/NA_{ijt} | Accounts payable to net assets. |
| DPA_{ijt} | Days in accounts payable outstanding. |
| $ERisk_{ijt}$ | The annual idiosyncratic risk is the standard deviation of the idiosyncratic returns calculated by from the monthly idiosyncratic returns from Eq. (4). |
| Q_{ijt} | Market value of equity ($PRCC_F \times CSHO$) plus the difference between total assets and book equity (<i>AT</i> - <i>CEQ</i>) to total assets. |
| $Q2_{ijt}$ | Market value of equity ($PRCC_F \times CSHO$) plus total debt (<i>DLC</i> + <i>DLTT</i>) plus value of preference shares (<i>PSTK</i>) to total assets. |
| $Capex_{ijt}$ | Capital expenditure (<i>CAPX</i>) to total assets. |
| $Dividend_{ijt}$ | Dividend (<i>DVC</i>) to total assets. |

Appendix B: The implications of mimicking for firm value

| Variables | Q | | Q2 | |
|-----------------------------|----------------------|----------------------|----------------------|----------------------|
| | Below | Above | Below | Above |
| | (1) | (2) | (3) | (4) |
| $\widehat{AR/TA}_{ijt-1}$ | 0.636** (0.324) | 0.040 (0.304) | 0.787** (0.316) | 0.281 (0.300) |
| $\widehat{AR/TA}_{ijt-1}^2$ | -3.016*** (0.793) | -1.167** (0.595) | -3.782*** (0.775) | -2.316*** (0.594) |
| $Cash_{ijt-1}$ | 1.456*** (0.063) | 2.150*** (0.112) | 1.476*** (0.059) | 2.014*** (0.107) |
| $Debt_{ijt-1}$ | -0.300*** (0.055) | -0.256*** (0.055) | -0.174*** (0.052) | -0.122** (0.054) |
| $Size_{ijt-1}$ | -0.013** (0.005) | -0.014*** (0.005) | -0.022*** (0.005) | -0.027*** (0.005) |
| PPE_{ijt-1} | -0.426*** (0.052) | -0.505*** (0.066) | -0.438*** (0.048) | -0.441*** (0.064) |
| SG_{ijt-1} | 0.737*** (0.048) | 0.831*** (0.047) | 0.721*** (0.044) | 0.841*** (0.044) |
| $Capex_{ijt-1}$ | 1.900*** (0.167) | 2.495*** (0.208) | 2.089*** (0.157) | 2.530*** (0.200) |
| $Dividend_{ijt-1}$ | 6.007*** (0.606) | 14.162*** (0.734) | 6.116*** (0.575) | 14.758*** (0.705) |
| Constant | 1.443*** (0.056) | 1.312*** (0.055) | 1.201*** (0.055) | 1.031*** (0.054) |
| N | 15,275 | 14,100 | 15,215 | 14,070 |
| Adj. R ² | 0.191 | 0.239 | 0.203 | 0.241 |

The table presents the estimation results of Eq. (5), which relates firm value to peer average trade credit and firm-specific characteristics. Q_{ijt} is the market value of equity ($PRCC_F \times CSHO$) plus the difference between total assets and book equity (*AT* - *CEQ*) to total assets. $Q2_{ijt}$ is the market value of equity ($PRCC_F \times CSHO$) plus total debt (*DLC* + *DLTT*) plus the value of preference shares (*PSTK*) to total assets. $\widehat{AR/TA}_{ijt-1}$ is the predicted peer average trade credit from the first stage of 2SLS. The firm-specific characteristics are defined as follows: $Cash_{ijt-1}$ is lagged cash and cash equivalent to total assets, $Debt_{ijt-1}$ is lagged debt to total assets, $Size_{ijt-1}$ is lagged size (logarithm of total assets), PPE_{ijt-1} is lagged fixed assets to total assets, SG_{ijt-1} is lagged sales growth, $Capex_{ijt-1}$ is lagged capital expenditure to total assets, and $Dividend_{ijt-1}$ is lagged dividends to total assets. $P_t Shock_{ijt}$ is the lagged peer idiosyncratic stock returns that are used as an instrument for the endogenous peer average trade credit. The peer firms' average characteristics are calculated as the average of all firms within an industry-year excluding the i^{th} observations. Industries are defined by the three-digit SIC codes. Below (Above) relates to firms that are categorized in the lower (upper) quartile of trade credit in each year. The sample consists of listed non-financial and non-utility firms in the United States drawn from *Compustat* over the period 1977–2016. All variables used are defined in

Appendix A and are winsorized at the lower and upper first percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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