Information Search Costs and Trade Credit:

Evidence from High-Speed Rail Connections

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Abstract: We investigate the impact of information search costs on firms' access to trade credit used as a major source of interfirm financing. Using the openings of high-speed rails (HSR) in China as exogenous shocks, we find that firms located in cities with HSR connections receive more trade credit from their suppliers. Further analyses show that the HSR effect on trade credit concentrates among customers with poor information transparency and that HSR openings improve the customers' information environment, suggesting that a decline in information search costs promotes supplier financing. Our finding reveals a positive externality of HSR construction on interfirm financing.

Keywords: Information search costs; Soft information; Trade credit; Interfirm financing; Supply chain financing; High-speed rail

JEL Codes: D8; D83; G14; G32

1. Introduction

Globally, trade credit is the most prominent source of interfirm financing for businesses, accounting for more than 90 percent of interfirm financing or more than 25 trillion US dollars in monetary terms worldwide (Costello, 2019; D'Mello and Toscano, 2020; Klapper et al., 2012; Petersen and Rajan, 1997). Contrary to the common perception that banks are the main credit suppliers in the debt market, Yang and Birge (2018) reveal that the sum of trade credit is in fact 1.3 times that of all the bank loans for non-financial firms in the US.[1] Meanwhile, using a large international sample of 34 countries, Levine et al. (2018) find that, on average, 25 percent of an average firm's total liability is financed by its suppliers in the form of trade credit.

Prior literature argues that the prevalence of trade credit is in part due to the suppliers' information advantage over financial institutions (Ng et al., 1999; Petersen and Rajan, 1997), implying that suppliers have exclusive access to private information that is not readily available to financial institutions. While the positive role of the information environment in facilitating the firms' access to capital from equity investors and creditors such as banks has been well documented (Armstrong et al., 2010; Bharath et al., 2008; Costello and Wittenberg-Moerman, 2011; Kim et al., 2011; Mansi et al., 2011), in contrast, there is limited evidence on how information, particularly the accessibility of private information, can affect interfirm financing activities through important stakeholders yet underexplored financiers of businesses, that is, suppliers. Although recent studies have attempted to investigate how financial reporting quality affects trade credit, the findings remain mixed (Chen et al., 2017; Li et al., 2021). More importantly, so far, these studies have primarily focused on public information, yet we still do not know whether and how private information, particularly the suppliers' costs of acquiring soft

[1] A distinctive feature of trade credit is that different from other sources of financing such as bank loans, the provision of trade credit does not typically involve a direct transfer of money from the creditor (i.e., the supplier) to the borrower (i.e., the customer). Instead, the suppliers offer such financing by effectively allowing the customer to delay the payment of the goods and services within a pre-specified period. Hence, trade credit is typically considered as informal and short-term financing offered by the suppliers to the customers (Bedendo et al., 2020; Kong et al., 2020c; Petersen and Rajan, 1997).

information[2], may affect the customers' access to trade credit and consequently shape customer-supplier relationships. Soft information is a relative concept to hard information (Liberti and Petersen 2019). Unlike hard information, such as financial statement, that is publicly disclosed and factually verified information in numbers, soft information contains information (mostly non-financial information) that would not typically be accessible unless obtained in person or exchanged in private (Liberti and Petersen 2019). Typical examples of soft information include corporate culture, employee morale and customer experience (Chen et al. 2022; Liberti and Petersen 2019).

To fill this gap, in this paper, to examine the impact of soft information on the firms' access to interfirm financing through suppliers, we exploit the quasi-experimental setting of the staggered openings of high-speed rail (HSR) lines across China, which significantly reduce the suppliers' costs in acquiring information about their customers. In the past decade, China has been rapidly expanding its HSR networks as an instrument to accelerate urbanization and stimulate growth in regional economies. Since HSR was first introduced in 2008, China has invested an unprecedented amount of 1.875 trillion RMB or 275 billion USD in its HSR networks (Ke et al., 2017). According to the China State Railway Group, as of July 2020, the total mileage of Chinese HSR networks has reached 36,000 kilometers, and this number is expected to surpass 70,000 kilometers by 2035 (Reuters, 2020). Widely considered as a more sustainable mode of transportation due to lower carbon emissions, high-speed trains substantially shorten journey times while providing a more punctual, reliable, and comfortable travel experience to passengers relative to that of other modes of transportation (Ke et al., 2017; Lawrence et al., 2019; Lin et al., 2020). Given the above advantages, the opening of HSR services can substantially improve labor mobility and interactions between people and entities from different cities (Chen et al., 2022; Zhang et al., 2020). Therefore, following Chen et al. (2022), we collect the

[2] Soft information is a relative concept to hard information (Liberti and Petersen 2019). Unlike hard information, such as financial statement, that is publicly disclosed and factually verified information in numbers, soft information contains information (mostly non-financial information) that would not typically be accessible and can only be obtained in person or exchanged through private interactions (Liberti and Petersen 2019). Typical examples of soft information include corporate culture, employee morale and customer experience (Chen et al. 2022; Liberti and Petersen 2019). In our study, soft information entails any useful information that a supplier can acquire only through a site visit that would not otherwise be available to the supplier.

completion dates of HSR lines in China and use the openings of HSR lines as natural experiments in China to study the impact of information search costs on the firms' access to interfirm financing along the supply chain.

There are two competing predictions regarding the impact of HSR openings on firms' access to trade credit. On the one hand, since trade credit is an unsecured loan for a limited time offered by suppliers, when making decisions on whether and how much trade credit should be offered, it is essential that suppliers have sufficient and high-quality information to assess the creditworthiness and default risks of customers (Ng et al., 1999; Petersen and Rajan, 1997). Chen et al. (2022) show that HSR openings reduce the costs of information acquisition for financial analysts and lead to more analyst visits, which will enable the discovery and dissemination of first-hand soft information (Cheng et al., 2019, 2016; Han et al., 2018). Building on this argument, we argue that the opening of HSR lines in the customers' home cities would reduce the journey time between customers and suppliers, making it more convenient and cheaper for suppliers to visit customers and acquire private information about their customers.[3] Moreover, the shortened journey time and lower costs of information collection also cut the costs of monitoring the customers' financial conditions, which will enable suppliers to reassess credit risks and identify potential defaults in a timely manner at the earliest opportunity (Ng et al., 1999). Taken together, we conjecture that the reduction in information acquisition costs following the openings of HSR lines is likely to reduce the information asymmetry between customers and suppliers and lower the suppliers' monitoring costs for customers. Hence, we predict that HSR openings can positively affect the firms' access to trade credit.

On the other hand, HSR may result in a reduction in trade credit. Prior literature suggests that there

[3] According to anecdotal evidence, it is very common for suppliers to regularly visit the headquarter of customers. For instance, it is reported that, on 27 October 2022, the suppliers of Kweichow Moutai Co. (600519) across China traveled to and gathered in Zunyi, Guizhou province (where the company is headquartered) and interacted and exchanged information with the senior management. More information can be found at http://www.gog.cn/zonghe/system/2022/10/27/018251238.shtml. Similarly, in another example, around 200 suppliers also traveled to the headquarter of Shenzhen Minglida Precision Technology Co., Ltd (301268) to attend the meeting and directly interact with the senior management of the listed firm. For more information, see http://stock.10jqka.com.cn/20221117/c642995435.shtml.

is a substitution relation between bank credit and trade credit (Burkart and Ellingsen, 2004; Chen et al., 2019; Shenoy and Williams, 2017). If indeed the information environment of the firms located in HSR cities has improved dramatically after the introduction of HSR lines, as Chen et al. (2022) implies, firms should have gained better access to capital through more formal channels, such as banks or equity markets. Thus, the increased access to bank credit and equity financing means that customers have less demand for or lower reliance on short-term credit from suppliers. Hence, it is also possible to experience a decline in trade credit after the establishment of HSR connections. Thus, the impact of HSR openings on trade credit is ultimately an important and relevant empirical question.

To answer our research question, we manually collect detailed information, including the opening date, operating speed, total distance, and total journey time, for all 106 HSR lines currently operating in China. Based on a large sample of 25,714 observations of 3,130 firms over the period of 2003-2018, we run a difference-in-differences (DiD) analysis and find that HSR connections lead to a significant increase in trade credit received, suggesting that HSR connections help local firms access more interfirm financing through suppliers. The results from our dynamic analysis reveal that the effect of HSR openings on trade credit starts to materialize in the first year after the treatment of HSR connections and persists into the second and third years following the opening of the HSR connections.

We then test whether the reduction in information search costs and improved accessibility to soft information from the suppliers' perspective is the underlying mechanism behind our main finding. Using financial reporting quality and analyst coverage as proxies for information asymmetry between customers and suppliers, we conduct subsample analyses and find that the positive impact of HSR openings on the level of trade credit received is more pronounced for customer firms whose information environment is poorer. In other words, given that when information asymmetry is high, due to higher credit risk, suppliers should be reluctant to extend trade credit to customers, the fact that more trade credit is offered to customers with higher information opacity implies that the introduction of HSR lines enables suppliers to access more information, particularly private information about the customers' financial positions, presumably due to the lower costs of visiting customers. We also directly test how HSR connections affect the local firms' overall information environment and find that HSR contributes to better financial reporting quality and more analyst followings, thereby allowing suppliers to access more original and high-quality information directly at much lower costs.

Moreover, given that the opening of HSR services between customers and suppliers can significantly shorten the journey time and through site visits, reduce the suppliers' costs in acquiring additional information about the customer, we test whether the effect of the HSR connection is stronger when the distance between the customers and the suppliers is within the optimal distance for the HSR journey, that is, within the distance in which the reduction in the information search costs of suppliers is perceived to be greater. In line with our expectation, we find that the increase in trade credit after the treatment of HSR connections is indeed greater when the distances between firms (i.e., customers) and their suppliers are within the optimal distance for HSR trips. Taken together, the above findings lend strong support to our "information search costs" conjecture that the decrease in the suppliers' information acquisition costs due to HSR connections facilitates information dissemination from customers to suppliers, which ultimately enhances the customers' access to trade credit. Subsequent subsample analyses demonstrate that the positive relation between HSR openings and the access to trade credit is more salient for non-state-owned firms, firms with a higher proportion of intangible assets, firms facing higher market competition, and when economic policy uncertainty is high.

While the DiD estimator enables us to draw a relatively strong causal inference, we conduct placebo tests and an instrumental variable (IV) analysis to further alleviate the endogeneity concerns that our results might be confounded by other local economic factors or events. First, to ensure that our results are indeed caused by the openings of HSR, we conduct two different placebo tests by repeating our main analysis using artificial times for HSR openings and an artificial treatment group selected through randomization. The insignificant results from both placebo tests confirm that our main results are attributable to the treatment of HSR connections. Second, by employing the historical total passenger number and altitude of the city as two instrumental variables for HSR openings, the results from two-stage least squares (2SLS) regressions suggest that the effect of the HSR connection on trade credit is likely to be causal.

We conduct a series of robustness checks and confirm that our results remain robust to alternative samples, including a propensity-score-matched (PSM) sample, the inclusion of additional control variables and fixed effects and alternative measures of trade credit. As a final analysis, we reveal that HSR-connected firms that receive high levels of trade credit can afford more investment and enjoy higher productivity.

Our paper contributes to the extant literature on various fronts. First, our study extends the literature on trade credit by empirically demonstrating that information search costs are an important determinant of trade credit. The existing literature has predominantly focused on the financial determinants of trade credit, but relatively limited evidence has emerged concerning the role of information in shaping trade credit policies. Thus, we fill this void by presenting novel evidence that the lower costs of soft information acquisition as a result of the upgrade in the transport infrastructure can boost interfirm financing. Additionally, given that HSR lines significantly reduce the journey time and enhance the convenience of intercity travel, our study also sheds light on how geographic proximity may influence the firms' access to financing provided by a key stakeholder of the firms, that is, their suppliers.

Second, our paper also contributes to a burgeoning line of literature examining the economic consequence of HSR networks as key infrastructures (e.g., Chen and Haynes, 2017; Diao, 2018; Gao et al., 2021; Ke et al., 2017; Kong et al., 2020b; Lawrence et al., 2019; Sun and Mansury, 2016). While the extant literature on HSR tends to focus on its valuation (Couto et al., 2015; Pimentel et al., 2012) and impact on regional economic growth and talent flows at the macroeconomic level (Diao, 2018; Ke et al., 2017; Kong et al., 2020b; Zhang et al., 2020), our finding shows that the opening of HSR lines can influence the individual firms' financing access and shape the financial interactions between customers and suppliers. Specifically, Chen et al. (2022) show that HSR can benefit financial analysts, as information intermediaries of capital markets, through information generation and forecast accuracy. Complementing the recent findings of Chen et al. (2022) and Kuang et al. (2021), our study offers original evidence on how HSR lines improve the suppliers' soft information acquisition and facilitate information dissemination along the supply chain, thus reducing the information asymmetry between customers and suppliers.[4]

Finally, our paper adds to the ongoing debate on the net benefit of HSR projects and has strong policy implications, as many countries around the world are weighing up the benefits and costs of building HSR networks. In particular, we believe our study provides a relevant and very timely reference to policymakers in the US and UK, where enormous investments in HSR networks are planned (BBC, 2020; Global Railway Review, 2020). In addition to the macroeconomic and sustainability benefits of HSR trains, our paper highlights another positive externality at the microeconomic level, that is, the facilitation of supply chain financing. More importantly, we demonstrate that firms with high levels of trade credit after HSR openings not only use extra financial resources to fund more investment but also enjoy superior firm productivity. Therefore, local governments may consider investing in transport infrastructure to enable local businesses, particularly those with limited financing access from capital markets, to attract more interfirm financing and to ultimately stimulate the investment in and the productivity of the local economy.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature and formulates our hypothesis. Section 3 describes the sample selection and research design. We present the empirical results in Section 4, and Section 5 concludes this study.

2. Related literature and hypothesis development

Prior literature has investigated the determinants of trade credit and identified several incentives from the suppliers' perspective (Cuñat, 2007; Long et al., 1993; Petersen and Rajan, 1997). First, trade credit

[4] The distinction and incremental contribution of our study of HSR effect on accounts payable relative to a parallel study by Chen and Liu (2019) of HSR effect on accounts receivable are as follows. First, our study focuses on the benefit of HSR on firms' external finance acquisition through the trade credit that they receive from their suppliers, while Chen and Liu (2019) evaluate the influence of HSR on product market competition through trade credit that firms provide to customers. Second, we show that firms benefit from HSR by receiving more trade credits from suppliers, and this effect is mainly driven by the reduction of information acquisition cost following HSR opening, while Chen and Liu (2019) show that HSR causes firms to offer less trade credit to customers, and this effect is mainly driven by the implicit guarantee of product quality following HSR opening. As such, our study differs from Chen and Liu (2019) in motivation, research question, and implication.

is widely used to attract more customers and stimulate demand by essentially offering a new external source of short-term financing for customers (Cuñat, 2007; Garcia-Appendini and Montoriol-Garriga, 2013; Guariglia and Mateut, 2016). Second, through the adjustment of trade credit policies, suppliers can also optimize business operations and mitigate seasonality in product demand by facilitating inventory flows and reducing the costs of holding excessive inventories (Bougheas et al., 2009; Daripa and Nilsen, 2011; Emery, 1987; Petersen and Rajan, 1997). Finally, trade credit also serves as an implicit guarantee of product quality to customers, especially when the product is relatively new to the market (Long et al., 1993; Petersen and Rajan, 1997). Despite the aforementioned benefits, suppliers, when extending credit to their customers, also bear additional financing and monitoring costs as well as the potential default risk (Ng et al., 1999). If customers fail to settle the payment within the agreed period, the suppliers may also incur subsequent costs in debt collection, liquidation and legal cases (Cuñat, 2007; Mateut et al., 2015). Thus, trade credit provision is ultimately an outcome of a rational economic decision made by suppliers after evaluating the associated costs and risks against the potential benefits.

Irrespective of the various motives behind the suppliers' decisions to extend credit to their customers, trade credit, in essence, is a type of informal and short-term loan provided by suppliers to customers (Bedendo et al., 2020; Kong et al., 2020c; Petersen and Rajan, 1997). Suppliers, similarly to other creditors, rely heavily on high-quality information to evaluate the credit risk of customers to decide whether to offer trade credit (Chen et al., 2017; Li et al., 2021). In fact, suppliers are exposed to greater risks than financial institutions that have additional measures to monitor the borrower and mitigate default risks (Kong et al., 2020c; Wu et al., 2014; Zhang, 2019). For example, banks can demand collateral and impose covenants in the debt contract, thereby managing the risk of bad debts and the cost of potential defaults. Therefore, suppliers have a higher demand for and a greater reliance on both public and private information regarding their customers' future economic prospects. The prior literature argues that due to their exclusive access to private information through daily operations, suppliers have information advantages over financial institutions (Burkart and Ellingsen, 2004; Cai et al., 2023; Hasan and Habib, 2023; Petersen and Rajan, 1997; Smith, 1987). By incorporating soft information gained through direct and frequent interactions with customers, suppliers may overcome information asymmetry and decide to offer trade credit to attract customers having limited access to formal sources of financing, such as bank loans (Asselbergh, 2002; Burkart and Ellingsen, 2004; Smith, 1987). Therefore, having sustainable access in a timely manner to soft information about customers is pivotal, as it allows suppliers to assess credit risk and monitor the financial solvency of customers, thus reducing the suppliers' risks and potential losses associated with such informal financing activities. It is also empirically supported that the availability of soft information increases the supply of financing and improves the customers' access to trade credit (Kong et al., 2020c; Liberti and Petersen, 2019).

How do HSR connections influence the firms' access to trade credit? Building on the prior literature, we conjecture that the introduction of HSR lines can improve the local firms' access to interfirm financing by significantly reducing suppliers' costs in obtaining soft information about customers. The introduction of the HSR network effectively reduces the geographic distance between two entities located in different cities by shortening the journey time of traveling from one city to another, thereby substantially reducing the costs of acquiring soft information via site visits (Petersen and Rajan, 2002). For example, Chen et al (2022) find that due to the lower information acquisition costs afforded by HSR, the opening of HSR leads to an increase in firm site visits conducted by financial analysts. Following this logic, we argue that the opening of an HSR line in a customer's headquartered city can also significantly reduce the journey time and effort required for a supplier to visit its customer, thus facilitating more frequent supplier visits to customers. Meanwhile, previous studies prove that the soft information acquired through private interactions and physical inspections during site visits is highly value-relevant (Cheng et al., 2019, 2016; Han et al., 2018). Therefore, the opening of HSR lines in the customers' cities would make it cheaper for suppliers to acquire more soft information, which would be highly valuable in evaluating the current financial condition, as well as the future liquidity risks of their customers, in a timely manner.

Moreover, the prior literature shows that geographic proximity is also beneficial for monitoring due to information advantages (Kedia and Rajgopal, 2011). Thus, a shorter journey time and an improved accessibility to soft information after HSR connections can also enable suppliers to engage at a lower cost in more effective monitoring of their customers' financial positions. When faced with lower costs of soft information acquisition and monitoring, suppliers can accurately evaluate and effectively monitor the customers' financial solvency and are thus more willing to offer trade credit to their customers located in HSR-connected cities.

Therefore, we conjecture that following the HSR openings, the increased accessibility to soft information and the reduced information asymmetry between suppliers and customers enables local firms to attract more trade credit from their suppliers. Hence, we present our main hypothesis below.

Hypothesis 1a. High-speed rail connections are positively associated with the firms' access to trade credit.

However, it is also possible that due to the potential substitution effect between trade credit and other financing channels, the amount of trade credit may decrease after HSR openings (Burkart and Ellingsen, 2004; Chen et al., 2019; Shenoy and Williams, 2017). The reduced journey times as a result of HSR openings also enable other capital providers, such as equity investors and financial institutions, to visit firms frequently and at a much lower cost. More importantly, prior studies have established that site visits are an effective way of accessing soft and private information that would not otherwise be available in capital markets (Cheng et al., 2019, 2016; Han et al., 2018). Therefore, an upgrade in the transport infrastructure can significantly enhance the information environment and transparency of local firms, which at the same time improves the firms' access to finance directly from equity investors and financial institutions (Armstrong et al., 2010; Bharath et al., 2008; Costello and Wittenberg-Moerman, 2011; Kim et al., 2011). Assuming there is a substitution effect between trade credit and other sources of financing (Burkart and Ellingsen, 2004; Chen et al., 2019; Shenoy and Williams, 2017), the increased access to bank credit will reduce the firms' demand for and reliance on trade credit, whose interest rates tend to be considerably higher than that for a comparable bank loan (Klapper et al., 2012; Ng et al., 1999).

Therefore, after HSR openings, we might expect a reduction in the trade credit received by firms and offer the competing hypothesis below.

Hypothesis 1b. High-speed rail connections are negatively associated with the firms' access to trade credit.

3. Data, variables, and methodology

3.1. Data

Our sample includes all firms listed in China's A-share market for the sample period from 2003 to 2018. Consistent with the prior literature (Chen et al., 2019; Fabbri and Klapper, 2016; Wu et al., 2014), we clean the initial sample and exclude the following: (1) firms listed in the financial industry (because of different accounting standards); (2) firm-year observations with negative total assets and stockholder equity; and (3) firm-year observations whose fundamental data needed to calculate trade credit and other control variables are missing. The final sample consists of 25,714 firm-year observations and 3,130 unique firms from 2003 to 2018. In addition, the firms in our sample are located in 237 prefecture-level cities across 31 provinces in China, indicating the representativeness of our final sample.

We collect detailed information on high-speed rails, including the line name, construction time, connection time, journey length, operating speed, and stations along the lines from the official website (http://news.gaotie.cn). From the official railway service website (https://www.12306.cn), as well as other online news sources, we verify the information on the stops along the existing lines. A city is defined as connected to a high-speed rail network if at least one high-speed rail station is present, while the connection year of the city is defined as the earliest year when a high-speed rail is operating. Through these procedures, we find that 198 cities were connected to the high-speed rail network at the end of 2018 (i.e., the treatment group), while the other cities remained unconnected (i.e., the control group).

In addition to the detailed information on high-speed rails, we obtain financial data and data on the firms' top five suppliers from the China Stock Market & Accounting Research database (CSMAR). We collect the firms' ownership structure data and institutional investor stock holding data from Wind.

Both CSMAR and Wind are widely used databases in studies on Chinese-listed firms. The prefecture-level socioeconomic data are drawn from the China City Statistical Yearbooks from 2004 to 2019.

3.2. Variables

3.2.1. High-speed rails

We define a dummy variable *HSR* as 1 if the firm-year observation is in the post-HSR connection period and as 0 otherwise; that is, for cities with HSR connections (i.e., the treatment group), *HSR* takes the value of 1 after the year in which the high-speed rail line is opened and takes the value zero before the HSR connection year. For cities that are not connected to the HSR network (i.e., the control group), *HSR* remains zero. Specifically, if the connection time is in the first half (before July 1st) of year t, we treat the high-speed rail connection year as year t; otherwise, we set the treatment year to be the following year at t+1 to allow the treatment effect to materialize (Chen et al., 2022; Kong et al., 2020a).

3.2.2. Trade credit

Following existing studies (Fisman and Love, 2003; Kong et al., 2020c), we define our key dependent variable, the firms' access to trade credit (*AccPay*), as the sum of notes payable, accounts payable and advance receipts divided by the total liabilities. We also measure trade credit in three other ways for robustness checks. First, following Fisman and Love (2003), we create the variable *AccPayNew1*, defined as the sum of notes payable, accounts payable and advance receipts divided by total assets. Second, consistent with Liu et al. (2016), we use the sum of notes payable, accounts payable and advance receipts divided by total operating income (*AccPayNew2*). Third, based on Ge & Qiu (2007), we sum up the notes payable, accounts payable and advance receipts, scaled by the total cost of goods sold (*AccPayNew3*), as the third alternative measure of trade credit.

3.2.3. Control variables

Consistent with recent studies on trade credit (Chen et al., 2022, 2019; Ge and Qiu, 2007; Wu et al., 2014), we include a vector of control variables to capture firm and city characteristics that are likely to affect the access to trade credit. At the firm level, we control for firm size (*Size*), leverage (*Lev*), firm age (*Age*), profitability (*ROA*), the sales growth rate (*Salesg*), market value (*TobinQ*), the cash holding ratio (*CashR*), a dummy indicating whether a firm is audited by a Big4 auditor firm (*Big4*). Moreover, given prior literature has shown that the agency problem and corporate governance can affect firms' access to external financing such as trade credit (Bastos and Pindado, 2007; Cai et al., 2022; Mande et al., 2012), we therefore include CEO duality (*Dual*), board size (*Boardsize*), the percentage of independent directors (*Indper*) to control for the quality corporate governance and the management expense ratio (*Manaexp*) to control for the agency cost (Ang et al., 2007; Cai et al., 2011; Huang et al., 2011). In addition, since a firm's access to trade credit may also be influenced by its local economic environment, we control for the economic factors of a firm's city, including the regional GDP (*TlGDP*), the per capita GDP (*PerGDP*), and the GDP growth rate (*GDPGrowth*). The detailed definitions of all variables used in this study are reported in Appendix A.

3.3. Descriptive statistics

Table 1 presents the sample distribution by year over the period of 2003-2018. To better reflect the expansion of the HSR network in China during our sample period, for the treatment sample (HSR=1) and the control sample (HSR=0), we also present the number of observations based on whether the firm is located in a city with an HSR connection in a certain year. In the earlier part of our sample (2003-2010), the observations concentrate predominantly in the control group since the number of HSR-connected cities was limited initially. However, after the State Council in China unveiled the massive HSR construction plan in 2008, more HSR lines were opened across the country, as reflected in the constant decline in the number of observations without HSR (the control sample). It is worth noting that, in 2011, the observations with HSR connections (the treated group) overtook those without HSR connections (the control group). Since then, the HSR network has continued to expand rapidly, indicating that an overwhelming majority of the listed firms are based in cities with HSR connections. As of 2018, approximately 94.8 percent (2,751 out of 2,901) of the firms in our sample have access to the HSR network, while, in contrast, merely 5 percent of the firms had no access to HSR in the control group. This growing trend is closely in line with the timings of the openings of HSR lines across China.

[Insert Table 1 here]

Table 2 reports the descriptive statistics for the final sample. All continuous variables are winsorized at the top and bottom 1%. Panel A presents the basic statistics for the variables in our main regression of the full sample. The mean and median ratios of the dependent variable *AccPay* are 0.3906 and 0.3576, respectively. The mean of the key independent variable *HSR* is 0.5954, indicating that approximately 59.54 percent of the firm-year observations receive the treatment of high-speed rail connections.

[Insert Table 2 here]

3.4. Regression models

To estimate the effect of the HSR connections on firms' access to trade credit, we follow Chen et al. (2022) and employ a difference-in-differences (DiD) approach by running the following regression model:

$$AccPay_{i,t} = \alpha_0 + \alpha_1 HSR_{i,t} + \alpha_n Controls_{i,t} + Firm/Year/City\ Fixed\ effects + \varepsilon_{i,t} \qquad (1)$$

where the dependent variable *AccPay* is the firms' access to trade credit measured by the sum of notes payable, accounts payable and advance receipts divided by total liabilities. The variable of interest is *HSR*, which captures the effect of staggered HSR openings on firms' access to trade credit. The vector *Controls* includes a series of control variables, described in the previous section, that capture other relevant firm-level and city-level factors.

To alleviate the concerns of omitted variable bias, we also include the firm fixed effects throughout our empirical analyses to control for unobservable time-invariant firm characteristics that may affect the access to trade credit. The year fixed effect is also included to eliminate common time trends. Finally, in addition to controlling for the economic variables of each city, we also include city fixed effects to account for any unobservable city-specific characteristics, such as local financial development or business culture, that might influence the opening of HSR and the firms' access to trade credit. Following the related literature (Abdulla et al., 2020; Chen et al., 2022), the standard errors are clustered at the firm level[5].

To analyze the impact of HSR openings on trade credit over time and test the parallel trend between the treatment and control groups prior to the event of HSR openings, we also run a dynamic model in Equation (2) as follows:

$$AccPay_{i,t} = \alpha_0 + \sum \alpha_\tau HSR_{i,t}^{\tau} + \alpha_n Controls_{i,t} + Firm/Year/City\ Fixed\ effects + \varepsilon_{i,t} \quad (2)$$

where $\sum HSR_{i,t}^{\tau}$ is a set of indicators for treatment firms in the event year relative to t (τ=-3, -2, -1, 0, 1, 2 and 3) and the other variables are defined as earlier. By showcasing how the effects of high-speed rails unfold over time, it enables us to verify the parallel-trend assumption underpinning the DiD research design. In other words, the trends for the treatment firms should be parallel to those of the control firms before the event such that the post-event changes for the treatment firms can be plausibly attributable to the high-speed rail connection.

4. Empirical Results

4.1. The effect of high-speed rails on the firms' access to trade credit

4.1.1. Main results

Table 3 presents the empirical results for our main analysis as specified in Equation (1), which examines the effect of high-speed rail connections on the firms' access to trade credit. Column 1 reports the estimation results when we include the firm, year and city fixed effects. Column 2 reports the results when we include the firm-level control variables, and we further include the city-level control variables in Column 3[6]. The coefficients on *HSR* are positive and statistically significant at the 1% level in all three columns, suggesting that the firms located in HSR-connected cities receive more trade credit after the openings of HSR. The coefficient is also economically significant. Compared to

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[5] Our untabulated analysis shows that the results remain unchanged using heteroscedasticity-robust standard errors.

[6] In an untabulated analysis, as a further robustness check, we also control for the bargaining power of suppliers using the share of purchase from top 5 suppliers following prior literature (Cai et al., 2022; Kong et al., 2020c). We find that our results remain robust after controlling for the bargaining power in the supplier-customer relationship. We thank the reviewer for kindly suggesting this test.

the control group without HSR, the treated firms receive 4.69% (=0.0183/0.3906) more trade credit after the opening of HSR. Taken together, these results are in line with *H1a* that high-speed rail connections have a positive and significant effect on the firms' access to trade credit[7]. For the control variables, the signs of the coefficients are largely consistent with those in prior literature (Kong et al., 2020c; Li et al., 2021; Wu et al., 2014). At the firm level, trade credit is negatively associated with size, leverage and the management expense ratio and positively associated with sales growth.

4.1.2. Parallel trend assumption test and dynamic effects

In the final column of Table 3, to test the parallel-trend assumption that is crucial to the causal inference of our DiD results, we run Equation (2), which effectively illustrates the dynamic effect of HSR openings on trade credit over a seven-year window around the event of HSR connection, that is, from three years before to three years after HSR openings. As reported in Column 4, all the indicators in the pre-treatment period (HSR^{-3}, HSR^{-2} and HSR^{-1}) are statistically insignificant, suggesting that there is no significant difference in the level of trade credit (*AccPay*) between the treatment group and control group prior to the event of the HSR connection. Hence, the important parallel trend assumption behind our DiD analysis is satisfied.

Instead, the increase in the treated group's trade credit relative to that of the control group appears only in the post-treatment period after the openings of HSR stations. Specifically, we find that HSR^{+1} becomes significant, suggesting that the effect of HSR on trade credit begins to materialize in the year after the opening of HSR. The significant coefficients for HSR^{+2} and HSR^{3+} indicate that the HSR effect becomes stronger from the second year and persists into the third year after HSR openings, implying that the openings of HSR have an enduring impact on interfirm financing. Overall, using a DiD approach, our baseline results suggest that HSR connections have a significantly positive effect on the firms' access to trade credit, which is in line with H1a.

[Insert Table 3 here]

[7] Results from our additional untabulated analysis suggest that the positive impact of HSR on trade credit is mainly driven by the increase in two types of trade credit, namely trade payables and advance receipts. We thank the reviewer for suggesting this analysis.

4.2. Potential mechanism

Thus far, we have shown consistent evidence that high-speed rail connections play an important role in improving the HSR-connected firms' access to trade credit. In this subsection, we explore the potential channels through which HSR connections can facilitate the firms' access to trade credit from suppliers. As explained earlier in the hypothesis development, we argue that the reduction in the suppliers' information search costs as a result of the improvement in the information environment following the treatment of HSR connections enables customers in HSR cities to attract more generous trade credit from their suppliers. Thus, we directly test the "information search costs" channel and provide evidence to support our conjecture.

4.2.1. Information search costs of suppliers

We first test whether the effect of HSR on trade credit varies with the suppliers' information search costs. Prior literature suggests that suppliers rely on high-quality and sufficient information about their customers to accurately assess the creditworthiness and default risks of the customers (Li et al., 2021; Ng et al., 1999; Smith, 1987). However, if a customer's information environment is poor, the supplier would face significantly higher costs in acquiring more information about the buyer, making it less viable for the supplier to offer trade credit (Kong et al., 2020c). Building on this logic, if, as we predict, the opening of the HSR line indeed reduces the suppliers' information search costs, the positive impact of HSR connections on trade credit should be more pronounced for customers whose financial information is either opaque or limited in financial markets, as HSR connections would be more relevant to these firms.

To test this information channel, we partition our sample into a high-information asymmetry group and a low-information asymmetry group by using two proxies for the information environment: financial reporting quality and analyst coverage. In Columns 1 and 2 of Table 4, we split the sample based on the dummy variable *HighEM*, set to one if the level of earnings management (*DA_ABS*) is above the yearly median and equals zero otherwise. In other words, firms with high levels of earnings management are classified as the high-information asymmetry group (*HighEM*=1), while firms with lower levels of earnings management are classified into the low-information asymmetry group

(*HighEM*=0). Consistent with our information search costs argument, our treatment dummy *HSR* is positively significant at the 1% level for firms with high levels of information asymmetry (*HighEM*=1), whose financial status and creditworthiness tend to be more obscure to suppliers. In contrast, the coefficient for *HSR* is insignificant for firms with low levels of information asymmetry (*HighEM=0*), whose financial reporting is considered more transparent. In Columns 4 and 5, we focus on the role of analyst coverage as an alternative proxy for the information environment of the customers. Based on whether analyst following (*AnaCov*) for the firm-year observation is above the yearly median value of analyst following, we classify firms into the high analyst coverage group (*HighAna*=1) and the low analyst coverage group (*HighAna*=0). Similarly, in line with our expectation, we find that the positive effect of HSR openings on trade credit concentrates only in firms with low analyst coverage and whose information search costs would be significantly higher, as indicated by the significant coefficient of *HSR* at the 1% level.

Therefore, the above subsample analyses on the role of the information environment provide consistent evidence that the positive impact of HSR connections on access to trade credit is more salient in firms with poorer information environments, where the information search costs of suppliers are perceived to be much higher. In other words, our results imply that firms with poor information quality are more likely to benefit from the openings of HSR, which would significantly lower the suppliers' costs in obtaining additional information regarding their customers and ultimately improve the customers' access to trade credit from their suppliers. Hence, these results suggest that the improvement in the information environment is likely to be a channel through which HSR openings influence the firms' access to trade credit.

Moreover, in Columns 3 and 6, by repeating the analysis with accrual-based earnings management (*DA_ABS*) and analyst coverage (*AnaCov*) being the outcome variables, we directly test whether HSR connections result in an improvement in the information environment. As illustrated in Column 3, the treatment dummy *HSR* is statistically significant and negatively associated with earnings management, indicating that HSR connections lead to a reduction in earnings management for firms located in HSR-connected cities compared to firms without access to the HSR network. In other words, this result suggests that firms in HSR cities improve their financial reporting quality after HSR connections. Consequently, by providing more transparent financial information to suppliers, the treated firms are more likely to attract more trade credit from suppliers.

In Column 6, the positive and significant coefficient of *HSR* shows that firms experience an increase in analyst following after HSR openings. This result complements a concurrent study by Chen et al. (2022), who show an increase in the number of analyst visits after HSR openings due to lower information acquisition costs for financial analysts. Taken together, HSR connections increase not only the number of analysts covering the firms but also the number of physical visits to firms in HSR-connected cities. Given that financial analysts are key information intermediaries that facilitate the dissemination of corporate information and the generation of new and value-relevant information to investors and other stakeholders, including suppliers, we argue that such an increase in analyst coverage after HSR connections would allow suppliers to directly access more valuable information about the customers' financial conditions without incurring significant information search costs and as a result of the improved information environment, would make them thus likely to offer more trade credit to customers.

Overall, in this section, we present consistent evidence that HSR openings lead to an improvement in the information environment of treated firms (*HSR*=1), which significantly reduces the suppliers' needs and costs in acquiring additional information about their customers. Therefore, our results lend direct support to our conjecture that the reduction in information asymmetry and consequently the information search costs for suppliers is the underlying mechanism through which HSR openings increase the firms' access to trade credit from suppliers.

[Insert Table 4 here]

4.2.2. Optimal travel distance

One underlying assumption behind our information channel is that an increase in the soft information exchange between customers and suppliers is at least partly due to more visits to customer firms being conducted by using high-speed trains, which significantly reduces the visitors' journey time and costs of site visits. In other words, the mere fact of opening an HSR line itself should not materially affect information dissemination unless more HSR journeys are made by the suppliers to visit the customers. To further substantiate the "information search costs" conjecture and ensure that it is indeed the HSR connections and subsequent use of high-speed trains between customers and suppliers that cause the increase in trade credit received by customers, we test whether such an effect is stronger if the distance between the cities and customers is within the optimal distance for HSR journeys. Prior literature suggests that the HSR is most suitable for medium-distance travel between 240 km and 1800 km (Liu et al., 2019).[8] Given that high-speed trains are used mostly for medium-distance trips, the opening of HSR lines should be most relevant and beneficial for firms or customer-supplier pairs that are within the optimal distance.

Empirically, we measure the geographic distance between a firm and its largest supplier[9] and construct an indicator variable ($Distance_{240\text{-}1800}$) equal to one if the distance between the firm and its largest supplier is within the optimal distance (240 km-1800 km) for the HSR journey. For comparison, we also include a dummy variable ($Distance_{>1800}$) equal to one if the customer-supplier distance is above 1800 km. Specifically, we interact the treatment dummy *HSR* with the distance indicators to capture how the effect of the HSR openings on the firms' access to trade credit varies with the geographic distance of customer-supplier pairs.

Table 5 presents the results. In line with our expectation, the key interaction term $HSR \times Distance_{240\text{-}1800}$ is positively significant at the 5% level under both specifications, suggesting that the positive effect

[8] This is in fact the journey distance that makes HSR most competitive and desirable to passengers. As an example, the Beijing-Shanghai line (1318 km) is proven to be very popular due to higher service frequency (over 100 pairs of high-speed trains daily), shorter total journey time (4 hour 24 minutes) and punctuality compared to those of other modes of transport (Lawrence et al., 2019). For shorter-distance trips below 240 km, travelers would prefer to travel by car or bus. For longer journeys beyond 1800 km, passengers would prefer to travel by air.

[9] We use the altitude and latitude coordinates of a firm's largest supplier obtained from Baidu Maps (https://map.baidu.com/) to measure the geographic distance between the firm and its largest supplier. However, given there is no mandatory and specific requirement on the disclosure of supplier names, most firms in our sample label their suppliers as "Supplier 1" and "Supplier 2" rather than disclosing the full names of their suppliers. As such, the identifiable information for the firms' largest suppliers is missing for many firms/observations in the dataset, and we end up with a smaller sample of 3,349 observations.

of HSR openings is indeed stronger when the geographic distance between the customer and its largest supplier is within the optimal distance for traveling by HSR trains. In comparison, we do not see such a differential effect if the customer-supplier pair is located more than 1800 km apart when the HSR is used less frequently, as evidenced by the insignificant and visibly smaller coefficient for $HSR \times Distance_{>1800}$. Together, the above results indicate that firms whose suppliers are located within the optimal travel distance receive significantly more trade credit after the treatment of HSR openings.

Therefore, given that high-speed trains are used most frequently for journeys within the optimal distance, our results also provide additional assurance that our baseline result can be plausibly attributed to the use of HSR services after HSR openings rather than to other factors. Furthermore, since HSR connections can substantially reduce the costs and time of suppliers to visit and collect soft information if their customers are located within the optimal distance and can be reached by high-speed trains, the fact that we find a stronger effect for customer-supplier pairs who are more likely to use the HSR network offers additional support to the "information search cost" channel.

[Insert Table 5 here]

4.3. Additional tests

Next, we provide further analysis of the relation between high-speed rail connections and the firms' access to trade credit by examining the heterogeneity in this relation. To conduct the analysis, we partition the sample into two subsamples based on several conditioning factors and rerun the regressions based on Equation (1). The results of the additional tests are presented in Table 6.

4.3.1. The role of state ownership

We first test how state ownership may alter the relation. Previous studies suggest that state-owned enterprises (SOEs) in China tend to have preferential access to credit from financial institutions and receive dedicated financial support from the government (Liu et al., 2016; Wu et al., 2014). In other words, compared to SOEs that have privileged access to financial resources, private firms (i.e., non-SOEs) are more reliant on informal financing channels such as trade credit. Given that SOEs have more financial resources and are less likely to face financing constraints, the positive effect of HSR connections on trade credit should be more relevant to private enterprises, which are more dependent on interfirm financing.

To test this heterogeneity, we split our sample based on whether the firm is a state-owned enterprise (*SOE*=1)[10] or a private enterprise (*SOE*=0). Columns 1 and 2 report the result. In line with our prediction, we find that *HSR* is positive and significant at 1% for non-SOEs (Column 1) and, in contrast, find an insignificant and smaller coefficient for *HSR* among SOEs (Column 2). Therefore, the more pronounced effect of HSR connections on access to trade credit concentrates in non-SOE firms is consistent with the argument that SOEs have superior financing access and lower dependence on informal financing.

4.3.2. The role of intangible assets proportion

Next, we explore the role of asset intangibility in the relation between HSR openings and access to trade credit. Barron et al. (2002) find that the level of intangible assets is associated with higher analyst uncertainty and a lower consensus among analysts' earnings forecasts, suggesting that evaluating the future economic outlook is more challenging for firms with a high proportion of intangible assets. Arguably, unlike analysts who are professional information intermediaries, suppliers need more private information to assess the liquidity and creditworthiness of customers with a high proportion of intangible assets. Thus, we expect that improved information accessibility as a result of HSR connections will be more valuable and relevant to suppliers when customers have higher levels of asset intangibility.

To test this, we construct a dummy variable *HighIntanP* equal to 1 if the proportion of intangible assets over total assets (*IntanP*) is above the yearly median and categorize the sample into high-intangible firms (*HighIntanP* =1) and low-intangible firms (*HighIntanP* =0). Columns 3 and 4 report the result. Compared with the insignificant result of *HSR* for low-intangible firms (Column 4), the effect of the HSR connection is indeed stronger in high-intangible firms, as illustrated by the positive and

[10] Following prior literature (Chen et al., 2011; Liu et al., 2016), we defined an SOE as a firm whose ultimate controlling shareholder is the government including central government, local governments, or other governmental agencies. The information regarding a firm's ultimate controlling shareholder is available from CSMAR database.

statistically significant coefficient of *HSR* in Column 3.

4.3.3. The role of industry competition

In Columns 5 and 6, we test how industry competition may influence the relation between HSR connections and the firms' access to trade credit. Suppliers perceive the credit risk of a customer to be higher if the firm is operating in a highly competitive industry, presumably due to greater uncertainty in its future performance and cash flows (Liu et al., 2016). In comparison, the credit risk of firms in industries with low levels of competition is considered to be much lower, meaning that they typically have better access to trade credit. Consequently, we expect that the improvement in information transparency induced by HSR connections is more important for customers operating in more competitive industries.

Specifically, we use the Lerner index to proxy for the level of market competition in a given industry (Gonçalves et al., 2018; Jory et al., 2020; Mueller et al., 2017). Essentially, the Lerner index (*Lerner*) is an inverse measure of industry competition, with a lower value in the Lerner index indicating a higher level of market competition. Based on the yearly median of the Lerner index, we thus partition the sample into a high industry competition group (*HighLerner*=0) and a low industry competition group (*HighLerner*=0). The results are reported in Columns 5 and 6. In line with our expectation, we find that our key variable *HSR* is positive and significant only for firms facing high levels of industry competition (Column 5), suggesting that the impact of HSR openings on access to trade credit is stronger for firms operating in highly competitive industries.

4.3.4. The role of economic policy uncertainty

Finally, we test whether the impact of HSR openings on trade credit varies with economic policy uncertainty (EPU). Recent studies show that firms are more reluctant to offer trade credit during periods of high uncertainty in economic policy (D'Mello and Toscano, 2020; Jory et al., 2020). When facing high economic uncertainty, suppliers have a greater demand for information about the future economic prospects of customers in order to make decisions on whether to offer trade credit to a particular customer. Given that HSR openings can significantly lower the suppliers' information search costs and improve the accessibility of soft information regarding their customers' solvency, the HSR effect should be more valuable and relevant when economic policy uncertainty is high. Thus, the association between HSR openings and trade credit should be stronger during high-EPU periods.

Consistent with recent studies (Li et al., 2020; Xia et al., 2020), we use the EPU index developed by Baker et al. (2016) to proxy for the level of economic policy uncertainty in China[11]. Subsequently, based on the yearly median of economic policy uncertainty (*EPU*), we partition our sample into a high-EPU group (*HighEPU*=1) and a low-EPU group (*HighEPU*=0). Columns 7 and 8 present the results of the subsample analysis on economic policy uncertainty. In line with our expectation, we find that *HSR* is positively significant at 1% in the high-EPU periods (Column 7) and, in contrast, find an insignificant result for HSR in the low-EPU periods (Column 8), suggesting that the relationship between HSR connections and trade credit is more pronounced during periods of high economic policy uncertainty.

[Insert Table 6 here]

4.4. Robustness tests

To ensure the robustness and reliability of our main results, we conduct a series of robustness checks and confirm that our results remain robust to a placebo test, an instrumental variable analysis, alternative samples, including a propensity-score-matched (PSM) sample, the inclusion of additional control variables and fixed effects and alternative measures of trade credit. The relevant tables and more detailed discussion on the results of our robustness tests are reported in the Supplementary Online Appendix.

4.5. Consequence analysis

Thus far, our findings suggest that firms located in HSR-connected cities receive more trade credit from suppliers. In this section, we explore how these firms can benefit from improved access to trade credit after HSR openings. To capture the effect of having high levels of trade credit for firms in HSR-connected cities, we interact the treatment indicator *HSR* with a dummy variable *HighAccPay*,

[11] The EPU index for China is accessible at https://www.policyuncertainty.com/scmp_monthly.html, at which a detailed description of the data construction process is also provided. Consistent with prior literature (D'Mello and Toscano, 2020; Li et al., 2020), we convert the monthly index into an annual measure by taking the average of the 12 monthly EPU values during the year.

which is equal to 1 if the sum of accounts payable (*AccPay*) is above the yearly median. The results are presented in Table 7.

First, we test whether the extra financing available to treated firms facilitates more investment. As indicated in Column 1, the key interaction term *HSR*×*HighAccPay* is positive and statistically significant at the 1% level, suggesting that firms that receive higher levels of trade credit following the openings of HSR maintain a significantly higher level of investment. We interpret this result as evidence that HSR-connected firms utilize extra credit to, at least partially, finance more investment.

In Column 2, we test whether firms receiving higher levels of trade credit following the treatment of HSR connections enjoy higher productivity. Prior literature has shown that improved access to financing can enhance the firms' productivity (Heil, 2018; Krishnan et al., 2015). Following previous studies (Giannetti et al., 2015; Krishnan et al., 2015), we use total factor productivity (*TFP*) to measure a firm's productivity and include *TFP* as the dependent variable in the regression. As shown by the regression results in Column 2, firms that receive higher levels of trade credit after HSR connections exhibit significantly higher productivity, as indicated by the positively significant coefficient for *HSR*×*HighAccPay*. This finding is consistent with prior literature (Heil, 2018; Krishnan et al., 2015) showing that an increase in credit supply can significantly enhance productivity at the firm level.

Taken together, in this section, we examine the economic consequence of receiving extra trade credit as a result of HSR openings and find that the increased access to trade credit due to HSR connections enables firms to engage in more investment and maintain higher firm productivity.

[Insert Table 7 here]

5. Conclusion

In this study, we investigate how HSR connections, as exogenous shocks to information search costs, affect the firms' access to trade credit. Using a difference-in-differences approach, we document consistent evidence that firms located in HSR-connected cities receive significantly more trade credit than firms located in cities without HSR lines. Further analyses suggest that the improvement in information accessibility and the reduction in information asymmetry between customers and suppliers is a plausible mechanism through which HSR openings can influence the firms' access to trade credit. The subsample analyses show that the effect of HSR openings on trade credit is stronger among non-state-owned firms, firms with a high degree of asset intangibility, firms facing high market competition, and when economic policy uncertainty is high. Our results remain unchanged after various endogeneity tests and robustness checks. Last, we also find that firms that receive generous trade credit from suppliers after HSR openings enjoy higher levels of investment and firm productivity.

Our paper makes multiple contributions. First, our paper contributes to the literature on trade credit. Unlike most literature that concentrates on the financial determinants of trade credit, our study highlights the important role of information dissemination across the supply chain in shaping trade credit decisions and the interactions between customers and suppliers. Meanwhile, our finding also points out that the advancement of the transportation infrastructure can also enhance the local firms' access to finance. Second, while economists and politicians have been mainly interested in the impact of the HSR network on economic growth and labor markets, our paper enriches the understanding of the externalities of HSR constructions at the microeconomic level (Chen et al., 2022; Kuang et al., 2021; Wang et al., 2019; Zhang et al., 2020). Specifically, adding to the ongoing debate on the net benefits of HSR projects, we demonstrate that the construction of HSR lines can promote interfirm financing and help local businesses attract more credit from suppliers.

Finally, our study has strong and relevant implications for policymakers. We reveal that the opening of HSR lines as a transportation infrastructure can play a positive role in local businesses in terms of broadening financing channels, stimulating more investment, and improving productivity. Despite the large capital investment required for HSR construction, in the next decades, HSR networks are expected to experience rapid expansion globally as a more sustainable mode of transportation. In light of the proposed HSR construction plans under contemplation in the US and UK (BBC, 2020; Mcfarland, 2020), our study provides timely evidence on the economic benefits of HSR projects and thus serves as a relevant reference to policymakers and regulators around the world.

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Table 1 Sample distribution

This table presents the sample distribution by year between the treatment group and control group.

Year	Treatment sample (HSR=1)		Control sample (HSR=0)		Total	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
2003	0	0	913	8.77	913	3.55
2004	21	0.14	932	8.96	953	3.71
2005	18	0.12	974	9.36	992	3.86
2006	19	0.12	963	9.26	982	3.82
2007	16	0.10	1032	9.92	1048	4.08
2008	68	0.44	1035	9.95	1103	4.29
2009	262	1.71	937	9.01	1199	4.66
2010	464	3.03	863	8.29	1327	5.16
2011	1020	6.66	650	6.25	1670	6.49
2012	1346	8.79	545	5.24	1891	7.35
2013	1534	10.02	500	4.81	2034	7.91
2014	1583	10.34	375	3.60	1958	7.61
2015	1806	11.80	210	2.02	2016	7.84
2016	2094	13.68	174	1.67	2268	8.82
2017	2307	15.07	152	1.46	2459	9.56
2018	2751	17.97	150	1.44	2901	11.28
Total	15309	100	10405	100	25714	100

Table 2 Descriptive statistics for variables and univariate analysis

Panel A reports the summary statistics for the variables included in our main regression model. Panel B reports the results of univariable analysis by testing the difference between treatment sample and control sample. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

Variables	N	Mean	Std	P25	Median	P75
AccPay	25714	0.3906	0.2304	0.2022	0.3576	0.5553
HSR	25714	0.5954	0.4908	0.0000	1.0000	1.0000
Size	25714	21.9464	1.2334	21.0554	21.7789	22.6345
Lev	25714	0.4460	0.2048	0.2850	0.4472	0.6026
Age	25714	2.6754	0.3998	2.3979	2.7081	2.9444
ROA	25714	0.0368	0.0552	0.0134	0.0348	0.0630
Salesg	25714	0.1932	0.4037	-0.0029	0.1283	0.2981
TobinQ	25714	1.9687	1.7520	0.8084	1.4400	2.4878
*Cash*R	25714	0.3390	0.1980	0.1884	0.2972	0.4539
Big4	25714	0.0635	0.2438	0.0000	0.0000	0.0000
Dual	25714	0.2168	0.4121	0.0000	0.0000	0.0000
Boardsize	25714	2.1657	0.2067	2.0794	2.1972	2.1972
Indper	25714	0.3678	0.0525	0.3333	0.3333	0.4000
Manaexp	25714	0.1026	0.0880	0.0486	0.0816	0.1245
T/GDP	25714	7.5627	8.4232	1.1443	3.7670	11.7151
PerGDP	25714	8.8056	4.4085	5.3023	8.3777	11.8198
GDPGrowth	25714	10.3464	3.6042	7.6000	9.4000	12.8000

Panel B: Univariate analysis

Variables	Treatment sample (*HSR*=1)		Control sample (*HSR*=0)		Difference in mean
	N	Mean	N	Mean	
AccPay	15309	0.4164	10405	0.3527	0.0637***
Size	15309	22.1308	10405	21.6750	0.4558***
Lev	15309	0.4264	10405	0.4750	-0.0486***
Age	15309	2.7903	10405	2.5064	0.2839***
ROA	15309	0.0382	10405	0.0348	0.0034***
Salesg	15309	0.1852	10405	0.2050	-0.0198***
TobinQ	15309	2.1449	10405	1.7095	0.4354***
*Cash*R	15309	0.3414	10405	0.3354	0.006**
Big4	15309	0.0656	10405	0.0603	0.0053*
Dual	15309	0.2660	10405	0.1444	0.1216***
Boardsize	15309	2.1340	10405	2.2123	-0.0783***
Indper	15309	0.3746	10405	0.3578	0.0168***
Manaexp	15309	0.1080	10405	0.0945	0.0135***
T/GDP	15309	10.6917	10405	2.9591	7.7326***
PerGDP	15309	11.1100	10405	5.4150	5.695***
GDPGrowth	15309	8.6910	10405	12.7820	-4.091***

Table 3 Effect of HSR connections on firms' access to trade credit

This table reports the regression results on the relation between HSR connections and trade credit. Columns 1-3 report the results from estimating Equation (1). In Column 4, we test the dynamic effect of HSR connections by running the model specified in Equation (2). We include *HSR* indicators for three years before, two years before and one year before (HSR^{-3}, HSR^{-2}, HSR^{-1}) as well as one year after, two years after and three or more years after (HSR^{+1}, HSR^{+2}, HSR^{3+}) the year of HSR connection (HSR^{0}). All other variables are defined in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	***Dep. Var: AccPay***			
	(1)	(2)	(3)	(4)
HSR	**0.0191*** **	**0.0176*** **	**0.0183*** **	
	(3.56)	**(3.55)**	**(3.75)**	
HSR^{-3}				-0.0062
				(-1.19)
HSR^{-2}				-0.0067
				(-1.10)
HSR^{-1}				0.0014
				(0.19)
HSR^{0}				0.0112
				(1.38)
$\boldsymbol{HSR^{+1}}$				**0.0150***
				(1.65)
$\boldsymbol{HSR^{+2}}$				**0.0238****
				(2.36)
$\boldsymbol{HSR^{3+}}$				**0.0227****
				(1.99)
Size		-0.0234***	-0.0233***	-0.0233***
		(-4.59)	(-4.57)	(-4.55)
Lev		-0.2788***	-0.2789***	-0.2794***
		(-15.30)	(-15.30)	(-15.32)
Age		-0.0927***	-0.0935***	-0.0938***
		(-4.61)	(-4.65)	(-4.68)
ROA		0.0557**	0.0556**	0.0543*
		(1.99)	(1.98)	(1.93)
Salesg		0.0110***	0.0109***	0.0109***
		(4.14)	(4.12)	(4.10)
TobinQ		-0.0010	-0.0011	-0.0011
		(-0.89)	(-0.90)	(-0.95)
*Cash*R		-0.0134	-0.0138	-0.0135

		(-1.21)	(-1.24)	(-1.21)
Big4		-0.0010	-0.0010	-0.0012
		(-0.09)	(-0.08)	(-0.10)
Dual		-0.0051	-0.0051	-0.0052
		(-1.03)	(-1.03)	(-1.05)
Boardsize		0.0129	0.0127	0.0126
		(0.88)	(0.87)	(0.86)
Indper		-0.0117	-0.0131	-0.0139
		(-0.29)	(-0.32)	(-0.34)
Manaexp		-0.2315***	-0.2316***	-0.2318***
		(-7.07)	(-7.07)	(-7.06)
T/GDP			-0.0003	-0.0005
			(-0.49)	(-0.67)
PerGDP			-0.0005	-0.0007
			(-0.44)	(-0.63)
GDPGrowth			0.0003	0.0003
			(0.52)	(0.55)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Observations	25,714	25,714	25,714	25,714
R-squared	0.7264	0.7545	0.7546	0.7547

Table 4 Potential mechanism

This table presents results on tests exploring the potential channel through which HSR openings affect access to trade credit. Specifically, we conduct subsample analysis based on earnings management (*DA_ABS*) in Column 1 and 2 and Analyst coverage (*AnaCov*) in Column 4 and 5. In Column 3 and Column 6, we directly test the effect of HSR openings on earnings quality (*DA_ABS*) and analyst coverage (*AnaCov*). Definitions of all variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Earnings management			Analyst coverage		
	AccPay		***DA_ABS***	***AccPay***		***AnaCov***
	(1)	(2)	(3)	(4)	(5)	(6)
	HighEM=1	*HighEM*=0		*HighAna*=0	*HighAna*=1	
HSR	0.0203***	0.0109	-0.0041**	0.0211***	0.0097	0.0464**
	(2.71)	(1.58)	(-2.34)	(3.15)	(1.58)	(1.99)
Size	-0.0388***	-0.0256***	-0.0011	-0.0268***	-0.0362***	0.5995***
	(-5.07)	(-2.99)	(-0.65)	(-4.17)	(-5.16)	(33.95)
Lev	-0.2314***	-0.2830***	0.0329***	-0.2641***	-0.2771***	-0.2976***
	(-8.09)	(-9.68)	(5.16)	(-11.74)	(-11.30)	(-4.45)
Age	-0.0756*	-0.0985***	-0.0182***	-0.0616**	-0.0871***	0.0558
	(-1.75)	(-2.91)	(-2.72)	(-2.06)	(-3.25)	(0.66)
ROA	0.1089**	0.0668	-0.1345***	0.0191	0.1118**	3.0477***
	(2.32)	(1.30)	(-6.61)	(0.53)	(2.12)	(18.95)
Salesg	0.0121***	0.0213***	0.0216***	0.0055	0.0131***	0.0230*
	(2.91)	(3.95)	(12.07)	(1.36)	(2.94)	(1.87)
TobinQ	-0.0006	0.0007	0.0039***	-0.0036*	0.0006	0.1316***
	(-0.28)	(0.35)	(6.54)	(-1.88)	(0.31)	(22.50)
CashR	-0.0399**	-0.0506***	0.0012	-0.0199	0.0058	0.0845*
	(-2.34)	(-2.84)	(0.29)	(-1.38)	(0.39)	(1.85)
Big4	0.0096	-0.0170	0.0019	0.0275	-0.0136	0.0559
	(0.60)	(-0.91)	(0.49)	(1.59)	(-1.06)	(1.14)
Dual	-0.0161**	-0.0009	0.0012	-0.0018	-0.0127*	-0.0179
	(-2.17)	(-0.12)	(0.62)	(-0.29)	(-1.93)	(-0.83)
Boardsize	0.0187	-0.0119	-0.0092**	0.0042	0.0266	0.1603***
	(0.93)	(-0.57)	(-2.04)	(0.21)	(1.42)	(2.76)
Indper	0.0075	-0.0032	0.0004	0.0081	0.0016	0.1159
	(0.12)	(-0.06)	(0.03)	(0.15)	(0.03)	(0.63)
Manaexp	-0.1624***	-0.3304***	0.0420***	-0.2864***	-0.3820***	0.3662***
	(-3.11)	(-6.20)	(3.17)	(-7.85)	(-6.10)	(3.20)
TlGDP	-0.0019*	0.0015	-0.0003*	-0.0011	0.0000	-0.0019
	(-1.84)	(1.52)	(-1.65)	(-1.11)	(0.01)	(-0.70)

PerGDP	0.0003	-0.0007	-0.0000	0.0008*	-0.0006	0.0017
	(0.64)	(-1.17)	(-0.24)	(1.67)	(-1.31)	(1.10)
GDPGrowth	0.0001	0.0000	-0.0000	-0.0000	0.0001	0.0006
	(1.06)	(0.28)	(-0.28)	(-0.21)	(0.66)	(1.36)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Observations	9,661	9,655	21,506	12,560	13,154	25,714
R-squared	0.7824	0.8200	0.2788	0.7602	0.8065	0.7454

Table 5 Optimal geographical distance

This table test how geographical proximity between customer and supplier would influences relation between HSR openings and access to trade credit. $Distance_{240\text{-}1800}$ is an indicator variable equal to one if the distance between the firm and its largest supplier is within the optimal distance (240km-1800km) for HSR journey. $Distance_{>1800}$ is an indicator variable equal to one if the distance between the firm and its largest supplier is beyond 1800km.Definitions of all other variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	***Dep. Var: AccPay***	
	(1)	(2)
$HSR \times Distance_{240\text{-}1800}$	0.0335**	0.0339**
	(2.01)	(2.04)
$HSR \times Distance_{>1800}$	0.0240	0.0248
	(1.05)	(1.09)
HSR	0.0148	0.0154
	(0.87)	(0.93)
$Distance_{240\text{-}1800}$	-0.0290*	-0.0288*
	(-1.93)	(-1.95)
$Distance_{>1800}$	-0.0250	-0.0249
	(-1.28)	(-1.29)
Size	-0.0405***	-0.0408***
	(-3.22)	(-3.23)
Lev	-0.3184***	-0.3192***
	(-6.81)	(-6.86)
Age	-0.0859	-0.0825
	(-1.22)	(-1.17)
ROA	-0.0575	-0.0583
	(-0.87)	(-0.88)
Salesg	0.0134	0.0137*
	(1.62)	(1.66)
TobinQ	-0.0018	-0.0019
	(-0.59)	(-0.61)
*Cash*R	-0.0082	-0.0082
	(-0.33)	(-0.32)
Big4	-0.0030	-0.0040
	(-0.13)	(-0.17)
Dual	-0.0188	-0.0194
	(-1.49)	(-1.53)
Boardsize	0.0149	0.0148
	(0.37)	(0.37)

Indper	0.1995*	0.1989*
	(1.75)	(1.74)
Manaexp	-0.2366**	-0.2356**
	(-2.56)	(-2.55)
TlGDP		0.0007
		(0.32)
PerGDP		-0.0006
		(-0.97)
GDPGrowth		-0.0001
		(-0.32)
Firm FE	YES	YES
Year FE	YES	YES
City FE	YES	YES
Observations	3,349	3,349
R-squared	0.8480	0.8481

Table 6 Cross-sectional tests

This table report the results of cross-sectional analyses based on state ownership (Columns 1 and 2), proportion of intangible assets (Columns 3 and 4), industry competition (Columns 5 and 6) and economic policy uncertainty (Columns 7 and 8). Detailed definitions of all variables are reported in Appendix A. The t-values, reported in the parentheses, are based on the standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	***Dep. Var: AccPay***							
	State Ownership		Intangible assets proportion		Industry competition		Economic policy uncertainty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SOE=0	*SOE*=1	*HighIntanP* =1	*HighIntanP* =0	*HighLerner* =0	*HighLerner* =1	*HighEPU*= 1	*HighEPU*= 0
HSR	0.0291***	0.0081	0.0186***	0.0088	0.0249***	0.0038	0.0184***	0.0115
	(3.82)	(1.32)	(2.90)	(1.21)	(4.12)	(0.52)	(3.30)	(1.56)
Size	-0.0256***	-0.0297***	-0.0260***	-0.0185**	-0.0355***	-0.0244***	-0.0312***	-0.0162**
	(-3.40)	(-4.28)	(-4.22)	(-2.31)	(-5.23)	(-3.37)	(-5.27)	(-2.26)
Lev	-0.3549***	-0.2082***	-0.3185***	-0.2433***	-0.3107***	-0.2253***	-0.3400***	-0.1773***
	(-13.90)	(-7.85)	(-14.00)	(-8.63)	(-12.39)	(-8.23)	(-16.51)	(-6.91)
Age	-0.1017***	-0.0404	-0.0757***	-0.0807**	-0.0543*	-0.1229***	-0.1120***	-0.0991***
	(-3.20)	(-1.19)	(-2.67)	(-2.19)	(-1.69)	(-3.32)	(-4.29)	(-3.19)
ROA	-0.0317	0.1476***	-0.0120	0.0825*	0.0446	0.0678	0.0077	0.0757
	(-0.80)	(3.13)	(-0.32)	(1.77)	(0.99)	(1.17)	(0.22)	(1.43)
Salesg	0.0009	0.0202***	0.0162***	0.0064*	0.0165***	0.0113***	0.0086**	0.0098**
	(0.24)	(5.43)	(3.97)	(1.70)	(3.90)	(2.79)	(2.39)	(2.18)
TobinQ	0.0014	0.0001	0.0004	0.0004	-0.0023	-0.0027	-0.0009	0.0010
	(0.82)	(0.03)	(0.22)	(0.19)	(-1.18)	(-1.33)	(-0.59)	(0.44)
*Cash*R	-0.0166	-0.0245	-0.0201	-0.0083	0.0195	-0.0172	-0.0096	-0.0017
	(-1.17)	(-1.48)	(-1.48)	(-0.51)	(1.18)	(-1.14)	(-0.80)	(-0.10)
Big4	-0.0201	0.0150	0.0120	-0.0325**	-0.0026	-0.0138	-0.0125	0.0030
	(-1.28)	(1.00)	(0.88)	(-2.21)	(-0.18)	(-0.74)	(-0.87)	(0.20)
Dual	-0.0075	-0.0012	0.0024	-0.0109	-0.0059	0.0005	-0.0093*	0.0030
	(-1.26)	(-0.15)	(0.45)	(-1.43)	(-0.91)	(0.06)	(-1.72)	(0.39)
Boardsize	0.0132	0.0064	0.0035	0.0425**	0.0149	0.0304	0.0195	0.0080
	(0.63)	(0.30)	(0.21)	(1.97)	(0.74)	(1.40)	(1.11)	(0.42)
Indper	0.0114	0.0035	-0.0594	0.0441	-0.0245	0.0231	-0.0006	-0.0469
	(0.19)	(0.06)	(-1.25)	(0.71)	(-0.42)	(0.35)	(-0.01)	(-0.84)
Manaexp	-0.3430***	-0.2965***	-0.2603***	-0.2914***	-0.3605***	-0.2635***	-0.3547***	-0.2908***

	(-7.63)	(-6.07)	(-6.87)	(-5.87)	(-7.63)	(-5.69)	(-7.41)	(-6.95)
TIGDP	-0.0008	-0.0001	-0.0016*	-0.0009	-0.0013	-0.0013	0.0014*	-0.0015
	(-0.70)	(-0.15)	(-1.75)	(-0.85)	(-1.22)	(-1.21)	(1.74)	(-1.33)
PerGDP	0.0008	-0.0015	0.0013	-0.0007	0.0004	-0.0008	0.0001	-0.0011
	(0.64)	(-0.88)	(1.04)	(-0.39)	(0.30)	(-0.53)	(0.08)	(-0.93)
GDPGrowth	-0.0007	0.0007	0.0001	-0.0001	0.0005	0.0004	-0.0015*	-0.0000
	(-1.01)	(1.08)	(0.13)	(-0.07)	(0.75)	(0.55)	(-1.76)	(-0.04)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,397	12,317	12,861	12,853	13,608	9,205	15,507	10,207
R-squared	0.7570	0.7755	0.7980	0.7863	0.7773	0.7787	0.8002	0.7893

Table 7 Consequence analysis

This table presents the results on the economic consequences for firms receiving trade credit after HSR connections. The outcome variables are investment expenditure (*Investment)* in Column (1) and total factor productivity (*TFP*) in Column (2). *HighAccPay* is a dummy variable equal to one if the level of trade credit received (*AccPay*) is above the yearly median and equal to zero otherwise. The detailed definitions of the other variables are reported in Appendix A. The t-values, reported in parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1)	(2)
	Investment$_{t+1}$	***TFP$_{t+1}$***
HSR×HighAccPay	0.0104***	0.0170*
	(4.12)	(1.86)
HighAccPay	-0.0048**	0.0144*
	(-2.19)	(1.88)
HSR	-0.0061**	0.0028
	(-2.38)	(0.32)
Size	-0.0094***	-0.0221***
	(-4.80)	(-3.18)
Lev	-0.0249***	0.0624**
	(-3.24)	(2.44)
Age	-0.0224**	-0.0183
	(-2.57)	(-0.59)
ROA	0.2068***	0.2845***
	(11.89)	(4.97)
Salesg	0.0017	0.0334***
	(1.16)	(6.35)
TobinQ	0.0058***	0.0015
	(7.62)	(0.65)
CashR	0.0462***	-0.0772***
	(8.40)	(-4.26)
Big4	0.0013	-0.0341**
	(0.24)	(-2.05)
Dual	0.0048**	0.0053
	(2.23)	(0.69)
Boardsize	0.0096	-0.0209
	(1.59)	(-1.01)
Indper	0.0122	0.0042
	(0.65)	(0.07)
Manaexp	-0.0181	-0.1975***

	(-1.43)	(-3.45)
TlGDP	0.0009***	0.0005
	(3.42)	(0.45)
PerGDP	0.0005	-0.0001
	(1.12)	(-0.09)
GDPGrowth	0.0006**	-0.0001
	(2.29)	(-0.11)
Firm FE	YES	YES
Year FE	YES	YES
City FE	YES	YES
Observations	22,665	22,582
R-squared	0.3995	0.4632

Appendix A Variable definitions and sources

Variable	Definition	Source
Firm-level variables		
HSR	Dummy variable equal to 1 if the firm-year is after the connection of the high-speed rails and equal to 0 otherwise. Specifically, if the connection time is in the first half of the year t (before July 1st), we treat the high-speed rails connection year as year *t* and as *t*+1 otherwise.	Manual collection
Treat	Dummy variable equal to 1 if a firm is from a prefecture-level city connected to high-speed rails network and equal to 0 otherwise.	Manual collection
Post	Dummy variable equal to 1 if a firm-year is from the post-HSR-connection period and equal to 0 otherwise.	Manual collection
AccPay	The sum of notes payable, accounts payable and advance receipts divided by total liabilities.	CSMAR
Size	Natural logarithm of total assets.	CSMAR
Lev	Total liabilities over total assets.	CSMAR
Age	Natural logarithm of the observed year minus the founding year plus one.	CSMAR
ROA	Total net earnings over total assets.	CSMAR
Salesg	Sales at year *t* minus sales at year *t*-1, divided by sales at year *t*-1.	CSMAR
TobinQ	The market value of the firm divided by the book value of total assets.	CSMAR
*Cash*R	Cash and short-term investments divided by total current assets.	CSMAR
Big4	Dummy variable equal to 1 if the firm is audited by an international Big 4 auditor and equal to 0 otherwise.	CSMAR
Dual	Dummy variable equal to 1 if the CEO also serves as board chairman and equal to 0 otherwise.	CSMAR
Boardsize	Natural logarithm of the number of directors on the board.	CSMAR
Indper	The number of independent directors on the board divided by the number of total directors.	CSMAR
Manaexp	Management expense over operating income.	CSMAR
DA_ABS	Absolute value of performance-match discretionary accruals estimated by using the Modified Jones Model following Kothari et al. (2005).	CSMAR
AnaCov	Number of analysts issuing earnings forecasts for the firm during the year.	CSMAR
Distance	Straight-line distance in kilometers between the two cities in which the supplier and customer are based.	Manual Collection
SOE	Indicator variable set to 1 if the firm is an SOE and set to	CSMAR

	zero otherwise.	
IntanP	Intangible assets proportion measured as total intangible assets divided by total assets.	CSMAR
Lerner	Industry Lerner index, for which a lower value indicates a higher level of market competition within an industry.	CSMAR
EPU	Economic policy uncertainty index for China based on South China Morning Post following the methodology of Baker et al. (2016).	policyuncertainty.com
Investment	Investment expenditure, calculated as (Cash paid to acquire fixed assets, intangible assets and other long-term assets + Net cash paid to acquire subsidiaries and other business units – Net cash received from disposal of fixed assts, intangible assets and other long-term assets – Net cash received from disposal of subsidiaries and other business units)/Total Assets	CSMAR
TFP	Total factor productivity at firm-year level calculated following Giannetti et al.(2015).	CSMAR
YearTrend	Discrete variable ranging from 1 to 16, calculated as the actual year minus 2002.	
City-level variables		
TlGDP	Total GDP at the city-year level.	China City Statistical Yearbook
PerGDP	GDP per capita at the city-year level.	China City Statistical Yearbook
GDPGrowth	The percentage of GDP growth at the city-year level.	China City Statistical Yearbook
Passen	Natural logarithm of number of total passengers using all modes of transportation in 1990 for the HSR-opening city	China City Statistical Yearbook
Altitude	Natural logarithm of the altitude of the HSR-opening city.	Manual Collection
RoadCargo	Natural logarithm of the annual volume of road freight for the city in the year.	China City Statistical Yearbook
AirCargo	Natural logarithm of the annual volume of civil air cargo for the city in the year.	China City Statistical Yearbook
RoadPassen	Natural logarithm of the total number of road passengers for the city in the year.	China City Statistical Yearbook
AirPassen	Natural logarithm of the total number of air passengers for the city in the year.	China City Statistical Yearbook
MobileUser	Natural logarithm of the total number of mobile phone users in the city during the year.	China City Statistical Yearbook
InternetUser	Natural logarithm of the total number of Internet broadband users in the city during the year.	China City Statistical Yearbook
Credit	Natural logarithm of the total balance (CNY) of loans provided by financial institutions in the city during the year.	China City Statistical Yearbook

Supplementary Online Appendices

Information Search Costs and Trade Credit:

Evidence from High-Speed Rail Connections

This section provides supplementary information and additional analyses as described below:

Appendix 1: Placebo test

Appendix 2: Instrumental variable approach

Appendix 3: Sensitivity test: Different samples

Appendix 4: Sensitivity test: Additional control variables and fixed effects

Appendix 5: Sensitivity test: Alternative measurements of trade credit

SA1. Placebo test

Thus far, our results present consistent evidence that the HSR connection leads to an increase in trade credit (*AccPay*). However, one might be concerned that our results might be confounded by other factors that may influence the decision on HSR construction. In other words, the treatment assignment, i.e., HSR opening, might not be exogenous but instead determined by the pre-existing economic conditions or the political status of a particular city (Faber, 2014).

To ensure that the increase in trade credit we documented can be attributed to the actual treatment of connections to the HSR network, we run a placebo test by repeating our main analysis by using a fictitious opening year for each HSR-connected city in our sample. Thus, we generate a dummy variable $HSR\_placebo^{-n}$, where n denotes the number of years before the actual year of each HSR opening. Specifically, we use the artificial HSR indicator based on two years, three years and four years before the real HSR opening year in Columns 1, 2 and 3, respectively. If our main results are indeed caused by the actual openings of HSR, we should not see significant results for any of the fictitious treatment dummy variables ($HSR\_placebo^{-n}$).

Panel A of Table A1 presents the results of the placebo test. In line with our expectation, we find that the coefficients for the fictitious treatment indicators are statistically insignificant and close to zero across all three columns, suggesting that our results are unlikely to be confounded by pre-existing factors before the HSR openings. Hence, our placebo test implies that the increase in trade credit can be plausibly attributed to the openings of the HSR network.

Furthermore, instead of using the actual cities experiencing HSR openings, we follow Cornaggia and Li (2019) and conduct another placebo test by randomly reselecting the treatment group (i.e., artificial cities with HSR openings), which essentially allows us to construct a fictitious group of HSR cities. As an illustration, if 4 cities (cities A, B, C and D) were connected to the HSR network in 2010, we would randomly select 4 artificial HSR cities out of all the cities in our sample, as if they did receive HSR connection treatment in 2010. To minimize the risk of coincidence and ensure that the treatment reassignment process is totally randomized, we repeat this process 1,000 times. Panel B reports the summary statistics for the coefficient and the T statistic for the HSR treatment variable. The coefficient is very close to zero, with mean and median values both at 0.001. In addition, the mean and median T values are well below the critical values, indicating that the treatment dummy *HSR* based on artificially generated "treated cities" is insignificant. We also plot the histogram of t-values estimated by replicating the regressions by 1,000 times. As depicted in Figure A1, the estimates from the placebo test are clustered around zero, showing that the significant effect of HSR openings on trade credit disappears when we replicate the analysis based on the artificial treatment group consisting of the randomly selected cities.

Therefore, the insignificant results of two placebo tests in Panel A and Panel B of Table A1 provide further assurance that the positive impact of HSR openings on trade credit that we documented in our baseline analysis is likely to be causal.

[Insert Table A1 here]

[Insert Figure A1 here]

SA2. Instrumental variable approach

While placebo tests provide strong evidence that the increase in trade credit can be plausibly attributable to HSR connections, it is still possible that the HSR connection itself may not be random, and our results may be contaminated by other factors. For example, the financial development of a city may both influence the firms' access to financing and imply that a city is more likely to raise enough capital to finance HSR projects. Thus, to further alleviate endogeneity concerns and tease out the effect of HSR connections on trade credit, we use an instrumental variable (IV) approach. Specifically, we focus on two instrumental variables: the historical number of total passengers (*Passen*) and the altitude (*Altitude*) of a city. First, we argue that the historical number of passengers using all modes of transport is a good reflection of the overall demand for high-speed trains, which is expected to be positively correlated with the probability of receiving the treatment of HSR connections. While cities with a large number of passengers historically are more likely to be connected to the HSR network, there is no reason to believe that the number of passengers in a city during a given year can affect the amount of trade credit received by a particular firm. Therefore, we consider the historical number of total passengers (*Passen*) as a valid instrumental variable. Furthermore, we also use city altitude as another instrument, which is an exogenous feature of a city (Zhang et al., 2020). While the altitude of a city can have significant implications for the feasibility and complexity of HSR construction, this geographic factor should not be able to directly affect the firms' access to trade credit. Thus, we use altitude (*Altitude*) as the second instrument for our IV analysis.

Table A2 presents the results of the two-stage least squares (2-SLS) regressions using the two instruments.[12] Panel A reports the results from the first-stage regressions at the city level where *HSR*, the treatment dummy, is the dependent variable. In addition to two instrumental variables, we also include GDP per capita (*PerGDP*) and GDP Growth (*GDPGrowth*) to control for economic development at the city level, as more economically developed cities are more likely to have a more advanced transportation infrastructure, such as the HSR network. Year fixed effects are also included to control for any year-specific events that may affect the propensity of receiving the treatment of the HSR connection. In line with our expectations, the results in the first-stage regressions (Columns 1-3) indicate that the total passenger number in a city is positively correlated with the propensity of HSR connections, while the altitude of a city is negatively correlated with the probability of HSR construction. Both instrumental variables are significant at 1% with the correct sign when controlled separately (Columns 1 and 2) as well as when included in the same regression (Column 3), which satifies the relevance assumption. Therefore, the results in Panel A, combined with the satisfaction of the exogeneity assumption based on the untabulated diagnostic test discussed in Footnote 1 below,

[12] Before our 2-SLS IV regressions, to ensure the validity of our instruments and confirm that the exclusion restriction is satified, we conduct a diagnostic test by effectively including our two instrumental variables in the baseline model using observations in 2003, the year before the opening of the first HSR line in China. The insignificant results for both instrumental variables suggest that the exogeneity assumption or the exclusion restrtiction is satisfied. For brevity, the results of the diagnostic test are not tabulated. We thank the reviewer for suggesting the diagnostic test.

collectively suggest that our two instrumental variables are valid. Panel B reports the results from the second-stage regressions. As illustrated in Columns 1-3 (Panel B), the results of the second-stage regressions show that $\widehat{HSR}$ remains consistently positive and statistically significant, which corroborates our main finding that HSR connections improve the firms' access to trade credit. Overall, our main finding persists when we adopt an IV approach to alleviate endogeneity concerns.

[Insert Table A2 here]

SA3. Alternative samples

To ensure that our main finding is not sensitive to a specific sampling procedure, we repeat our main regression model by using a number of alternative samples. The results based on various alternative samples are reported in Table A3.

- *Propensity-score-matched sample*

First, to ensure that the treated group (*HSR*=1) and control group (*HSR*=0) were comparable prior to the treatment of HSR openings and to address selection bias, we used the propensity score matching (PSM) technique to construct an alternative sample. Specifically, for each HSR-connected (i.e., treated) city, we match a non-HSR (i.e., control) city based on a number of city characteristics in the year preceding the treatment by using the nearest-neighbor algorithm with replacement.[13] After obtaining the matched pairs of HSR cities (*Treat*=1) and non-HSR cities (*Treat*=0), we then merge with the firm-year panel dataset to obtain our PSM sample. We construct a dummy variable *Post* set to 1 if the fiscal year is after the year of HSR connection and interact it with the treatment indicator *Treat* to form our key interaction term *Treat*×*Post* in the regression. As reported in Column 1, the interaction

[13] The matching covariates include total GDP, GDP per capita, and GDP growth rate at t-1, with t being the treatment year, as well as the historical transport volume in 1990. To ensure the quality of matching, we allow matching with replacement to identify the best possible match in terms of city characteristics for each HSR-connected city. Thus, one city may have been matched and may have appeared more than once in the PSM sample, as evidenced by the slightly larger sample size in Column 1.

term of interest *Treat*×*Post* is positive and statistically significant, confirming a positive impact of HSR openings on the trade credit received.

- *Excluding province-level cities and provincial capitals*

Second, one may still be concerned that megacities and cities of political and economic importance, such as provincial capitals, are more likely to receive the treatment of HSR connections, which would undermine the exogeneity of our treatment, i.e., HSR openings. To address this concern, in Column 2, we eliminate observations for firms that are located in province-level cities and provincial capitals from our original sample. As shown in Column 2, *HSR* remains positively significant after removing economically and politically important cities.

- *Excluding firms listed after HSR openings*

Third, we remove firms listed after HSR connections, which are included constantly in the treated group. The removal of these firms would ensure that each firm has at least one observation both before and after the treatment of HSR connections. The positive and statistically significant result for *HSR* in Column 3 suggests that our result is robust to the exclusion of firms listed after the treatment of HSR connections.

- *Shorter window of (-5,5) around events*

Fourth, we keep observations that are within 5 years before and after the HSR openings. The use of a shorter window around the event of HSR connections (i.e., treatment) would allow us to have a more balanced sample while reducing the potential interference caused by observations that are remote from the event of HSR connections in the regression. Our results in Column 4 remain unchanged under this shorter window.

- Suppliers located in HSR cities

Finally, we keep observations where suppliers are located in HSR cities using the supplier information disclosed by the listed firms. The rationale behind this alternative sample is that if the positive effect of openings of HSR on trade credit is due to improved soft information dissemination from listed firms to the suppliers, such effect is expected to be significant and pronounced when both the supplier and the customer (i.e., listed firm) are based in HSR-connected cities. Consistent with our expectation, results in Column 5 remain robust to this alternative sample where both suppliers and customers have access to HSR services.

[Insert Table A3 here]

SA4. Additional controls and fixed effects

In this section, we further test the robustness of our results by controlling for additional city-level characteristics as well as additional fixed effects. To address the concern that our results might be confounded by the accessibility of other modes of transportation or the advancement in IT infrastructures over time, in Column 1, we include a set of city-level variables, including the volume of freight by road (*RoadCargo*), volume of freight by rail (*RailCargo*), the volume of freight by air (*AirCargo*), the number of road passengers (*RoadPassen*), the number of rail passengers (*RailPassen*), the number of flight passengers (*AirPassen*), the number of mobile phone users (*MobileUser*), and the number of broadband internet users (*InternetUser*). In Column 2, we further control for bank credit availability (*Credit*) at the city-year level, as financial development and accessibility of credit from financial institutions can influence the firms' trade credit decisions (Fisman and Love, 2003). In Column 3, we further include a time trend variable *YearTrend*[14] to control for any potential linear movement in our outcome variable (i.e., trade credit) over our sample period.

Moreover, we also test the robustness of our main results by including additional sets of fixed effects. In Column 4, in addition to the *firm*, *year* and *city* fixed effects in our baseline specifications, we also include *industry-by-year* fixed effects to account for time-varying industry features that may influence the level of trade credit received. Last, in Column 5, we add *province-by-year* fixed effects in our

[14] *YearTrend* is a discrete variable ranging from 1 to 16 derived from the actual year of each firm-year observation. Since our sample starts from 2003 to 2018, we assign values to YearTrend by counting the sequence of the year in our sample period. For example, *YearTrend* takes a value of 1 (16) for observations in the year of 2003 (2018), which is the first (last) year of our sample.

regression model to control for any economic or social factors at the provincial level over time that may affect the firms' access to trade credit.

The regression results are reported in Table A4. We find that the key variable of interest *HSR* is persistently positive and significant at the 1% level, thus indicating that our baseline finding is robust to the inclusion of additional control variables and fixed effects.

[Insert Table A4 here]

SA5. Alternative measures of trade credit

As a final robustness test, to ensure that our results are not accidentally driven by a specific measure of trade credit, we repeat the main regression model by using three alternative measures of trade credit. The results based on the alternative measures are reported in Table A5. Column 1 presents the regression results based on *AccPayNew1*, defined as the sum of notes payable, accounts payable and advance receipts divided by lagged total liabilities. In Column 2, we use *AccPayNew2*, measured as the sum of notes payable, accounts payable and advance receipts deflated by lagged total assets (Chen et al., 2019; Wu et al., 2014; Xu et al., 2021), as the dependent variable. In Column 3, we repeat the analysis using *AccPayNew3,* calculated as the sum of notes payable, accounts payable and advance receipts, scaled by lagged total revenue. In Column 4, we repeat the analysis using *AccPayNew4,* defined as accounts payables scaled by the ratio of cost of goods sold to 365 (Abdulla et al., 2017; Garcia-Appendini and Montoriol-Garriga, 2013; Jory et al., 2020; Love et al., 2007; Zhang, 2019).

In line with our baseline results, our key variable *HSR* remains positive and significant across all four columns, confirming that our main results are robust to alternative proxies for trade credit as the dependent variable.

[Insert Table A5 here]

Reference (Supplementary Online Appendices)

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Figure A1 Placebo plot

This figure presents the distribution of t-value generated when simulating the analysis in Table A1 by 1,000 times.

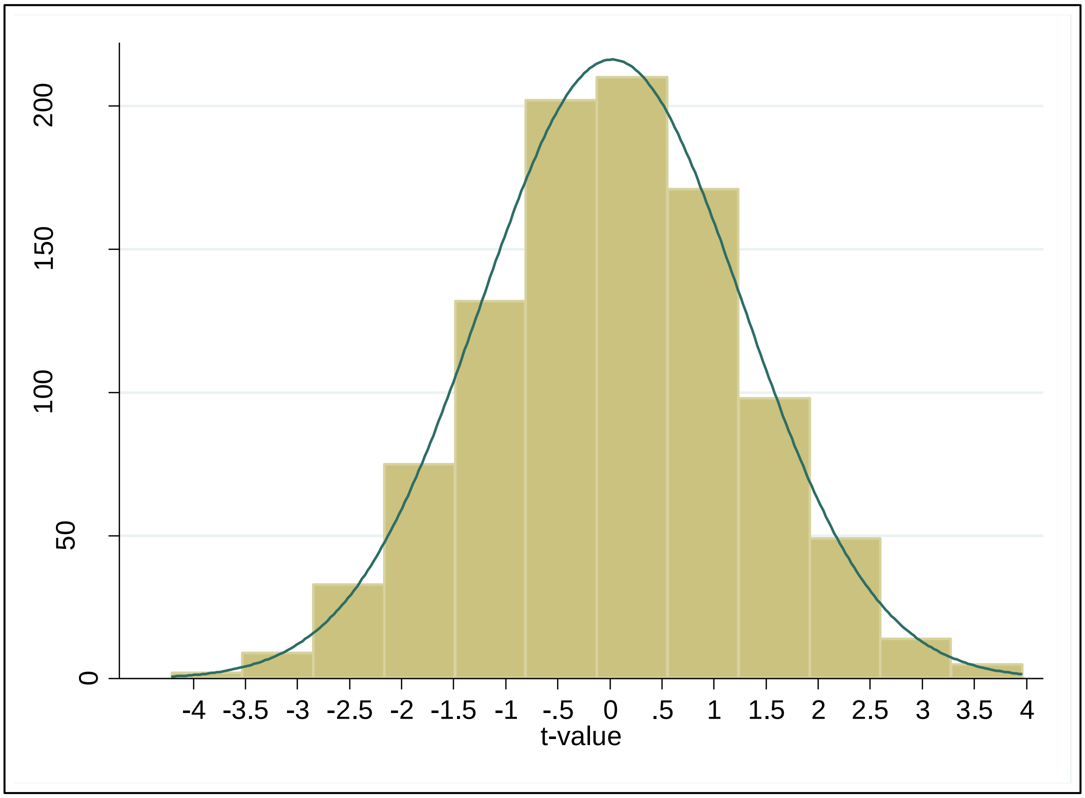

Table A1 Placebo test

This table reports the results of the placebo tests. Panel A presents results based on artificial year of HSR connections. Specifically, we use the artificial HSR indicator based on two years, three years and four years before the real HSR opening year in Columns 1, 2 and 3, respectively. *HSR_placebo*$^{-2}$ is an indicator set to one if the artificial treatment year is two year before the actual year of HSR openings. *HSR_placebo*$^{-3}$ is an indicator set to one if the artificial treatment year is three years before the actual year of HSR openings. *HSR_placebo*$^{-4}$ is an indicator set to one if the artificial treatment year is four years before the actual year of HSR openings. Panel B presents the estimates from 1000 replications using the artificial treatment group consisting of randomly selected cities for the treatment of HSR connections. Definitions of other variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Artificial year of treatment

Variables	***Dep. Var: AccPay***		
	(1)	(2)	(3)
HSR_placebo^{-2}	0.0042		
	(0.79)		
HSR_placebo^{-3}		-0.0037	
		(-0.66)	
HSR_placebo^{-4}			-0.0089
			(-1.51)
Size	-0.0258***	-0.0257***	-0.0256***
	(-5.11)	(-5.09)	(-5.07)
Lev	-0.2778***	-0.2779***	-0.2779***
	(-15.31)	(-15.33)	(-15.33)
Age	-0.0939***	-0.0947***	-0.0953***
	(-4.20)	(-4.23)	(-4.26)
ROA	0.0506	0.0500	0.0495
	(1.64)	(1.62)	(1.61)
Salesg	0.0087***	0.0087***	0.0086***
	(3.11)	(3.10)	(3.09)
TobinQ	-0.0006	-0.0006	-0.0006
	(-0.41)	(-0.41)	(-0.41)
*Cash*R	-0.0114	-0.0112	-0.0111
	(-1.03)	(-1.01)	(-1.00)
Big4	-0.0014	-0.0015	-0.0015
	(-0.11)	(-0.13)	(-0.13)
Dual	-0.0052	-0.0053	-0.0053
	(-1.05)	(-1.07)	(-1.08)

Boardsize	0.0143	0.0139	0.0137
	(0.97)	(0.95)	(0.93)
Indper	-0.0085	-0.0092	-0.0098
	(-0.21)	(-0.22)	(-0.24)
Manaexp	-0.3350***	-0.3357***	-0.3356***
	(-10.16)	(-10.16)	(-10.14)
TlGDP	-0.0003	-0.0003	-0.0004
	(-0.49)	(-0.49)	(-0.54)
PerGDP	-0.0000	-0.0000	-0.0001
	(-0.05)	(-0.03)	(-0.05)
GDPGrowth	0.0002	0.0002	0.0002
	(0.41)	(0.33)	(0.42)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
Observations	25,714	25,714	25,714
R-squared	0.7560	0.7560	0.7560

Panel B: Artificial treatment group

Stats	N	Mean	Std	P5	P25	Median	P75	P95
Coefficient	1000	0.0001	0.0065	-0.0109	-0.0042	0.0001	0.0044	0.0107
t-value	1000	0.0196	1.2556	-2.1467	-0.8255	0.0247	0.8591	2.1033

Table A2 Instrument variable analysis

This table reports the results from 2-stage least squares regressions using two instrumental variables: *Passen* and *Altitude*. Panel A reports the results of first-stage regression at city-year level with treatment dummy *HSR* being the dependent variable. Panel B presents the results of second-stage regression at firm-year level, with *AccPay* being the outcome variable. The IV estimations using *Passen* and *Altitude* as the instrument are presented in Column 1 and Column 2, respectively. In Column 3, both instruments are included in the first-stage regression. *Passen* is defined as the number of total passenger number using all modes of transport in the city in 1990. *Altitude* is the altitude of the city. Definitions of all variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: The first-stage regression

Variables	Dep. Var.: *HSR*		
	(1)	(2)	(3)
Passen	0.7370***		0.6551***
	(5.20)		(4.61)
Altitude		-0.3516***	-0.2968***
		(-4.20)	(-3.36)
PerGDP	0.1483***	0.1275***	0.1046**
	(3.42)	(2.72)	(2.38)
GDPGrowth	0.0109	0.0278	0.0201
	(0.44)	(1.25)	(0.87)
Year FE	YES	YES	YES
Observations	2,106	2,106	2,106
Pseudo R-squared	0.285	0.271	0.311

Panel B: The second-stage regression

Variables	Dep. Var.: *AccPay*		
	(1)	(2)	(3)
$\widehat{HSR}$_*Passen*	0.0850***		
	(3.03)		
$\widehat{HSR}$_*Altitude*		0.0596**	
		(2.32)	
$\widehat{HSR}$_*PasAlt*			0.0575**
			(2.54)
Size	-0.0287***	-0.0289***	-0.0288***
	(-5.46)	(-5.51)	(-5.50)

Lev	-0.3175***	-0.3171***	-0.3172***
	(-16.77)	(-16.77)	(-16.76)
Age	-0.0960***	-0.0981***	-0.0967***
	(-4.26)	(-4.36)	(-4.29)
ROA	0.0343	0.0359	0.0352
	(1.09)	(1.14)	(1.12)
Salesg	0.0096***	0.0097***	0.0097***
	(3.17)	(3.21)	(3.20)
TobinQ	-0.0013	-0.0013	-0.0013
	(-0.90)	(-0.89)	(-0.88)
*Cash*R	-0.0114	-0.0110	-0.0114
	(-1.04)	(-1.00)	(-1.04)
Big4	-0.0037	-0.0037	-0.0038
	(-0.34)	(-0.33)	(-0.34)
Dual	-0.0084*	-0.0083*	-0.0083*
	(-1.75)	(-1.72)	(-1.72)
Boardsize	0.0124	0.0126	0.0125
	(0.82)	(0.83)	(0.83)
Indper	-0.0137	-0.0145	-0.0136
	(-0.34)	(-0.36)	(-0.34)
Manaexp	-0.3567***	-0.3561***	-0.3563***
	(-10.07)	(-10.04)	(-10.07)
TIGDP	0.0003	-0.0000	0.0001
	(0.40)	(-0.02)	(0.12)
PerGDP	-0.0007	-0.0000	0.0004
	(-0.63)	(-0.03)	(0.41)
GDPGrowth	0.0000	-0.0001	0.0001
	(0.08)	(-0.22)	(0.11)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
Observations	21,231	21,231	21,231
R-squared	0.7786	0.7785	0.7786

Table A3 Sensitivity test: Different samples

This table reports OLS regression results on the relation between HSR openings and trade credit based on alternative samples. Column 1 report results based on a propensity score matched (PSM) sample using the nearest-neighbor algorithm with replacement. *Treat* is equal to one if the firm is located in an HSR-connected city in the sample, zero otherwise. *Post* is equal to one if the year of observation is after the year of HSR opening. In Column 2, we exclude observations where the firm is located in province-level cities and provincial capitals from the sample. In Column 3, we exclude observations where firms started listing in the stock exchange after the treatment of HSR connection. In Column 4, we restrict the observations to be within the window of (-5, 5), i.e., up to five years before and after the year of the HSR opening. In Column 5, we restrict the observations to a smaller sample of firms whose suppliers are also headquarterd in HSR-connected cities. the Detailed definitions of all variables are reported in Appendix A. The t-values, reported in the parentheses, are based on the standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dep. Var: AccPay				
Variables	PSM sample	Excluding province-level municipality and provincial capital	Excluding firms listed after HSR connection	Short window [-5, +5]	Suppliers located in HSR cities
	(1)	(2)	(3)	(4)	(5)
Treat×Post	0.0383**				
	(2.12)				
Post	-0.0117				
	(-0.89)				
HSR		0.0186**	0.0160***	0.0128**	0.0475**
		(2.58)	(3.30)	(2.49)	(2.23)
Size	-0.0206***	-0.0287***	-0.0247***	-0.0314***	-0.0428***
	(-3.05)	(-4.20)	(-4.72)	(-5.16)	(-2.95)
Lev	-0.2707***	-0.3295***	-0.2577***	-0.2700***	-0.3197***
	(-8.87)	(-12.26)	(-13.61)	(-12.50)	(-5.69)
Age	-0.0722**	-0.1082***	-0.0951***	-0.1217***	-0.1525
	(-2.04)	(-3.35)	(-4.09)	(-4.90)	(-1.60)
ROA	0.0148	-0.0152	0.0717**	0.0312	0.0071
	(0.31)	(-0.34)	(2.23)	(0.81)	(0.13)
Salesg	0.0088***	0.0081	0.0100***	0.0124***	0.0125
	(2.73)	(1.61)	(3.48)	(3.56)	(1.55)
TobinQ	0.0024	-0.0009	-0.0014	-0.0027*	-0.0009
	(0.91)	(-0.44)	(-0.92)	(-1.72)	(-0.37)
*Cash*R	0.0186	-0.0061	-0.0101	0.0066	-0.0098

	(0.98)	(-0.38)	(-0.86)	(0.52)	(-0.34)
Big4	-0.0001	-0.0013	-0.0011	-0.0102	-0.0225
	(-0.00)	(-0.08)	(-0.09)	(-0.69)	(-0.93)
Dual	-0.0070	-0.0008	-0.0043	-0.0053	-0.0208*
	(-1.38)	(-0.12)	(-0.81)	(-0.98)	(-1.70)
Boardsize	0.0108	0.0018	0.0131	0.0177	0.0235
	(0.62)	(0.09)	(0.86)	(1.07)	(0.56)
Indper	-0.0122	-0.0571	-0.0179	0.0157	0.1687
	(-0.24)	(-1.03)	(-0.42)	(0.33)	(1.45)
Manaexp	-0.3019***	-0.4337***	-0.3247***	-0.3774***	-0.2434***
	(-8.12)	(-7.90)	(-9.69)	(-8.83)	(-2.60)
T/GDP	-0.0004	-0.0031**	-0.0003	-0.0002	0.0018
	(-0.54)	(-2.21)	(-0.46)	(-0.19)	(0.62)
PerGDP	0.0002	0.0002	-0.0008	0.0003	-0.0000
	(0.13)	(0.56)	(-0.72)	(0.52)	(-0.01)
GDPGrowth	-0.0004	-0.0004	0.0001	-0.0007	-0.0018
	(-0.45)	(-0.71)	(0.19)	(-1.31)	(-1.09)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Observations	27,084	12,267	22,010	17,366	2,650
R-squared	0.7505	0.7538	0.7396	0.7951	0.8754

Table A4 Sensitivity test: Additional control variables and fixed effects

This table reports the regression results after the inclusion of additional control variables (Columns 1 and 2) and fixed effects (Columns 3 and 4) in the baseline model. Definitions of all variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	*Dep. Var: AccPay*				
	(1)	(2)	(3)	(4)	(5)
HSR	0.0181***	0.0175***	0.0160***	0.0167***	0.0230***
	(3.79)	(3.66)	(3.64)	(3.40)	(3.48)
Size	-0.0281***	-0.0286***	-0.0320***	-0.0248***	-0.0259***
	(-5.27)	(-5.37)	(-6.20)	(-5.06)	(-5.29)
Lev	-0.2625***	-0.2652***	-0.2522***	-0.2891***	-0.2909***
	(-13.83)	(-13.93)	(-13.25)	(-16.06)	(-16.19)
Age	-0.0923***	-0.0886***	-0.0528**	-0.0970***	-0.1059***
	(-3.91)	(-3.75)	(-2.31)	(-4.04)	(-4.30)
ROA	0.0646*	0.0656*	0.0905**	0.0249	0.0237
	(1.84)	(1.85)	(2.55)	(0.79)	(0.75)
Salesg	0.0121***	0.0125***	0.0092***	0.0088***	0.0094***
	(4.17)	(4.28)	(3.15)	(3.07)	(3.30)
TobinQ	-0.0020	-0.0023	-0.0018	-0.0006	-0.0011
	(-1.40)	(-1.64)	(-1.58)	(-0.39)	(-0.79)
CashR	-0.0024	-0.0024	0.0086	-0.0113	-0.0095
	(-0.21)	(-0.21)	(0.74)	(-1.03)	(-0.88)
Big4	-0.0001	-0.0005	-0.0027	-0.0017	-0.0017
	(-0.01)	(-0.04)	(-0.22)	(-0.15)	(-0.14)
Dual	-0.0051	-0.0050	-0.0037	-0.0021	-0.0034
	(-0.98)	(-0.96)	(-0.70)	(-0.43)	(-0.71)
Boardsize	0.0203	0.0219	0.0249	0.0183	0.0172
	(1.32)	(1.42)	(1.60)	(1.31)	(1.23)
Indper	-0.0027	-0.0010	0.0276	-0.0131	-0.0192
	(-0.06)	(-0.02)	(0.63)	(-0.33)	(-0.49)
Manaexp	-0.3422***	-0.3415***	-0.3664***	-0.3367***	-0.3431***
	(-10.04)	(-10.02)	(-10.76)	(-10.21)	(-10.36)
TlGDP	-0.0004	-0.0003	-0.0012	-0.0007	0.0017
	(-0.45)	(-0.40)	(-1.49)	(-0.98)	(0.99)
PerGDP	-0.0004	-0.0006	0.0003	-0.0004	-0.0005
	(-0.41)	(-0.54)	(0.45)	(-0.38)	(-0.33)
GDPGrowth	0.0003	0.0003	0.0010**	-0.0001	-0.0010*

	(0.50)	(0.56)	(2.00)	(-0.22)	(-1.78)
RoadCargo	-0.0012	-0.0012	0.0015		
	(-0.19)	(-0.18)	(0.22)		
AirCargo	-0.0000	-0.0002	0.0002		
	(-0.09)	(-0.36)	(0.36)		
RoadPassen	-0.0016	-0.0014	0.0102***		
	(-0.75)	(-0.65)	(5.55)		
AirPassen	-0.0004	0.0006	0.0015		
	(-0.35)	(0.56)	(1.39)		
MobileUser	-0.0028	-0.0028	0.0009**		
	(-0.64)	(-0.65)	(2.46)		
InternetUser	0.0023	0.0025	0.0033		
	(0.54)	(0.58)	(0.77)		
Credit		-0.0006	0.0112**		
		(-0.11)	(2.16)		
YearTrend			0.0066***		
			(2.93)		
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES
City FE	YES	YES	YES	YES	YES
Industry×Year FE	NO	NO	NO	YES	YES
Province×Year FE	NO	NO	NO	NO	YES
Observations	22,646	22,361	22,361	25,714	25,714
R-squared	0.7621	0.7631	0.7644	0.7756	0.7815

Table A5 Sensitivity test: Alternative measurements of trade credit

This table presents results of baseline regressions using alternative measures of trade credit as outcome variable. *AccPayNew1* is defined as the sum of notes payable, accounts payable and advance receipts divided by lagged total liability. *AccPayNew2* is defined as the sum of notes payable, accounts payable and advance receipts divided by lagged total assets. *AccPayNew3* is defined as the sum of notes payable, accounts payable and advance receipts divided by lagged total revenue. *AccPayNew4* is defined as accounts payables scaled by the ratio of cost of goods sold to 365. Detailed definitions of other variables are reported in Appendix A. The t-values, reported in the parentheses, are based on standard errors corrected for serial correlation at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	*AccPayNew1*	*AccPayNew2*	*AccPayNew3*	*AccPayNew4*
	(1)	(2)	(3)	(4)
HSR	**0.0211*** **	**0.0069** **	**0.0172* **	**4.2419* **
	(2.65)	**(2.22)**	**(1.83)**	**(1.67)**
Size	0.0302***	0.0240***	0.0861***	22.6775***
	(3.93)	(7.22)	(8.01)	(7.16)
Lev	0.0506*	0.2954***	0.6814***	163.6336***
	(1.82)	(24.34)	(20.57)	(16.27)
Age	-0.3164***	-0.0625***	-0.2002***	-66.8774***
	(-9.97)	(-5.17)	(-5.77)	(-5.54)
ROA	0.3825***	0.2641***	0.3849***	177.5372***
	(6.17)	(9.49)	(8.89)	(9.93)
Salesg	0.0000***	0.0000***	0.0000***	-10.9838***
	(7.58)	(12.05)	(14.61)	(-5.54)
TobinQ	0.0022	0.0029***	0.0070***	-1.7504**
	(1.10)	(8.92)	(3.11)	(-2.19)
*Cash*R	0.0204	0.0050	0.0244	7.4455
	(1.11)	(0.72)	(1.18)	(1.25)
Big4	-0.0028	-0.0136	-0.0427*	-9.9174
	(-0.14)	(-1.44)	(-1.93)	(-1.44)
Dual	0.0070	-0.0017	0.0019	0.5999
	(0.85)	(-0.56)	(0.21)	(0.23)
Boardsize	0.0120	0.0061	-0.0078	-1.0960
	(0.52)	(0.64)	(-0.31)	(-0.15)
Indper	-0.0529	-0.0203	-0.0140	17.7286
	(-0.86)	(-0.82)	(-0.20)	(0.92)
Manaexp	-0.0001	-0.0001*	-0.0001	103.8987***
	(-0.53)	(-1.72)	(-0.48)	(4.23)
TlGDP	-0.0014	0.0001	0.0019	0.9633***

	(-1.39)	(0.18)	(1.51)	(2.61)
PerGDP	-0.0031*	-0.0012*	-0.0007	0.1376
	(-1.78)	(-1.82)	(-0.32)	(0.24)
GDPGrowth	0.0007	0.0003	-0.0006	-0.1003
	(0.81)	(0.91)	(-0.61)	(-0.35)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Observations	25,714	25,714	25,714	25,714
R-squared	0.5827	0.8088	0.6995	0.6952