Price Dynamics and the Financing Structure of Firms in Emerging Economies[*]

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Abstract

We use a novel dataset that merges goods-level prices underlying the CPI in Mexico with the balance sheet information from Mexican publicly listed firms and study the connection between firms' financing structure and price dynamics in an emerging economy. First, we find that larger firms (in terms of sales and employees) tend to use more interfirm trade credit relative to bank credit. Second, these firms use interfirm trade credit as a mechanism to smooth variations in their prices. Third, all else equal, firms with a higher trade-to-bank credit ratio tend to lower prices. In turn, the behavior of these firms explains the negative relationship between aggregate trade credit growth and inflation in the data. A tractable New Keynesian model with search frictions in physical

input markets sheds light on firms' structural characteristics as well as the economic mechanisms that rationalize the empirical findings.

JEL Classification: E24, E32, G18, O17
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1 Introduction

Identifying the determinants and drivers of aggregate price dynamics is essential not only to understand the transmission channels of monetary policy but also to implement effective policies. Amid the rising importance of financial markets in shaping real economic activity and the role of financial disruptions during the Great Recession, recent studies have highlighted the role of financial frictions in understanding aggregate price dynamics in the advanced economies (AEs).[1] Other studies have explored how the economy's sectoral structure influences the transmission of U.S. monetary policy, and the link between heterogeneity in sectoral price rigidities and business cycle fluctuations (Bouakez, Cardia and Ruge-Murcia, 2009). However, there is surprisingly little work on the determinants of inflation dynamics in emerging economies (EMEs) beyond the role of domestic supply shocks, exchange rate movements, oil prices, and external shocks (see, for example, Choi, Furceri, Loungani, Mishra and Poplawski-Ribeiro, 2018).

In particular, little is known about the role, if any, of differences in the financing structure of firms in EMEs for price dynamics. This issue is non-trivial since the financing structure of firms in EMEs differs from the one in AEs in one striking way: amid limited access to the banking system and formal credit markets, firms in EMEs display a greater prevalence of trade credit—that is, interfirm financing relationships that take place outside of formal credit markets and the banking system—as a source of external financing.[2] For example, the average trade credit share—that is, the share of trade credit as a percent of firms' external financing—is roughly 60 percent among Latin American small firms, while the bank credit share is only 30 percent (Burkart *et al.*, 2011).[3] In contrast, firms in AEs tend to rely comparatively more on bank credit and other formal sources. While interfirm trade credit is most widespread among small firms (which represent the bulk of firms in EMEs), larger firms also tend to rely heavily on interfirm trade credit relationships

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[1] See Kimura (2013) for Japan, Montero and Urtasun (2001) for Spain, and Gilchrist, Schoenle, Sim and Zakrajšek (2017) for the United States.

[2] See Allen, Carletti, Qian and Valenzuela (2013) for cross-country evidence. For seminal work on trade credit, see Petersen and Rajan (1997). Burkart and Ellingsen (2004) and Burkart, Ellingsen and Giannetti (2011) discuss theoretical rationales behind the existence of trade credit contracts.

[3] See McMillan and Woodruff (1999) for work on informal credit and interfirm relationships in Vietnam and Ayyagari, Demirguc-Kunt and Maksimovic (2010) for the interaction between formal and informal finance in China. IFC, Financial Inclusion Experts Group, SME Finance Sub-Group (2010); Stein, Ardic and Hommes (2013); Global Financial Development Report (2014) discuss evidence on the credit gap between firms and the extent of informal sources of external finance in developing economies and EMEs.

despite enjoying better access to formal credit markets. To the extent that firms' financing structure affects the effective cost of inputs and therefore influences firms' cost structure, a natural question is whether the high prevalence of trade credit usage among EME firms has implications for firms' price-setting and, ultimately, inflation dynamics. This paper provides an empirical and theoretical characterization of the link between firms' financing structure—with a focus on the role of interfirm trade credit relationships as a prominent source of external financing—and price dynamics in the context of an extensively-studied EME, Mexico.

We use a novel dataset that merges goods-level prices underlying the Mexican consumer price index (CPI) with detailed balance sheet information from Mexican publicly-traded firms and study the connection between firms' financing structure and price dynamics in an EME. Our empirical results show that the use of interfirm trade credit, in particular its growth, is an important determinant of price dynamics in Mexico, even after controlling for other plausible factors that may influence inflation. More specifically, our empirical findings are fourfold. First, larger firms (in terms of sales or employees) in our sample tend to use more interfirm trade credit, manifested in firms' account payables, relative to bank credit. In other words, these firms have a higher trade-to-bank-credit ratio relative to other firms. Second, firms with a higher trade-to-bank-credit ratio tend to rely on trade credit usage as a mechanism to smooth variations in their prices: all else equal, there is a negative and statistically significant relationship between trade credit growth and firm-specific inflation among these firms, even after controlling for other characteristics (including firm size), while a similar link is absent among low trade-to-bank-credit ratio firms. Prices decrease by 2 percent after a 1 percent increase in trade-credit growth for firms with high trade-to-bank credit. Third, the negative relationship between trade credit growth and inflation is observed at the aggregate level—that is, when both firms with a high and low trade-to-bank-credit ratio are included in the sample. This suggests that it is high trade-to-bank-credit ratio firms that explain the negative relationship between trade credit growth and price dynamics in the data. Fourth, bank-credit growth does not play a significant role for inflation dynamics for firms of any size.

To shed light on firms' financial structure characteristics as well as the economic mechanisms behind these empirical findings, we build a tractable New Keynesian model with search frictions in physical input markets in order to capture interfirm trade credit relationships. In our framework, input suppliers accumulate physical inputs and supply them to perfectly-competitive intermediate goods firms via matching markets. We consider matched physical inputs as trade credit given that costly search and long-lived relationships underlie the supply of physical inputs to firms. Intermediate goods firms use these physical inputs and household-supplied labor to produce. Monopolistically-competitive final goods firms purchase intermediate goods and choose their price subject to price rigidities. This simple model can successfully replicate the (qualitative) negative relationship between trade credit growth and inflation for a high trade-to-bank credit economy, and the non-significant relation of these two variables in the low trade-to-bank credit ratio economy, as

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well as the negligible correlation of bank credit growth and inflation. More importantly, numerical experiments with aggregate productivity and monetary policy shocks suggest that firms' share of trade-credit-based inputs in the production process—a structural feature of the economy that is unobservable in our data and, importantly, a parameter that shapes firms' trade-to-bank-credit ratio—is critical to generate the empirical fact that firms with a higher trade-to-bank-credit ratio exhibit a stronger negative relationship between trade credit growth and inflation dynamics.

The intuition behind our results is as follows. To fix ideas, consider a positive aggregate productivity shock. As a standard New Keynesian model, this shock brings a reduction in the marginal cost, which prompts a decrease in inflation. However, because we model interfirm trade credit relationships, an economy with a high trade-to-bank credit ratio behaves differently than one with a low trade-to-bank credit ratio. Relative to an economy with a low trade-to-bank credit ratio (as a result of a lower share of search-based physical inputs in production), a high-ratio economy exhibits a sharper reduction in inflation and an initially larger increase in trade credit growth relative to a low trade-to-bank credit ratio economy. The intuition behind this result traces back to the fact that high trade-to-bank-credit ratio firms' search for physical input suppliers (and hence the demand for such inputs) is more sensitive to shocks. Amid higher steady-state physical input usage in the high trade-to-bank credit economy, the demand for physical inputs in response to an increase in aggregate productivity is larger relative to an economy with a low steady-state trade-to-bank credit ratio. Because of firms using more trade credit vis-à-vis bank credit, there is a larger amount of resources spent searching for suppliers relative to the amount of resources available. As a result, tightness in the market decreases and so do physical input prices. Ultimately, all input prices initially contract more, leading to a larger reduction in marginal cost and therefore inflation relative to a low-ratio economy. Thus, economies with a high steady-state trade-to-bank credit ratio exhibit a stronger negative relationship between trade credit growth and inflation, as in the data. A similar general mechanism is at play amid monetary policy shocks.

Our work is related to the literature on trade credit and relationship lending (Cuñat, 2007; Uchida, Udell and Watanabe, 1997), to recent studies that have explored the interaction between trade credit, nominal rigidities, and monetary policy (Mateut, Bougheas and Mizen, 2006; Pasten, Schoenle and Weber, 2016, Petrella et al., 2016), and to the behavior and determinants of inflation in EMEs (Mohanty and Klau, 2001; Gagnon, 2009; Capistrán and Ramos-Francia, 2009; Osorio and Unsal, 2013).[4]

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[4] Also, see Fisman and Love (2003) for the link between trade credit and industry growth; Heise (2016) for the role of interfirm relationships in price stickiness. Shao (2017) argues that trade credit reduces financial frictions on average, but may exacerbate business cycle fluctuations. Altinoglu (2018) and Luo (2017) show how interfirm trade credit affects aggregate fluctuations by contributing to the creation of linkages that channel propagation of shocks. Finkelstein Shapiro (2014) and Finkelstein Shapiro and González Gómez (2017) show a connection between trade credit, self-employment, and business cycle persistence, and trade credit and firm leverage dynamics, respectively, in environments where trade credit is rooted in capital

Altunok, Mitchell and Pearce (2015) characterize how trade credit affects the effectiveness of monetary policy in the United States, while Guariglia and Mateut (2006) study the link between trade credit, bank credit, inventory investment, and monetary policy in the United Kingdom. Rudanko (2017) formally characterizes the link between search-based frictional product markets and price-setting behavior. In addition, our paper is related to recent work on search frictions, customer capital, and price-setting behavior (Rudanko, 2017; Gilbukh and Roldan, 2017). Importantly, existing studies on price-setting behavior and trade credit have centered primarily on AEs. Moreover, those studies that consider search frictions focus primarily on the customer capital side rather than on the input-supply side. To the best of our knowledge, we are the first to empirically show and highlight the relevance of trade credit for price-setting in an EME context, where trade credit is more prevalent as an external financing source, as well as the first to consider physical-input-based search frictions amid price rigidities.

Most generally, our work contributes to a growing literature on the microeconomic characteristics, including firms' financing structure, that determine inflation dynamics and shed light on the transmission channels of monetary policy, both in AEs and in EMEs. Thus, closest to our work are Gilchrist *et al.* (2017), who characterize the link between inflation dynamics and firms' financial constraints during the Great Recession in the United States. Relative to their work and other existing studies, we not only focus on price dynamics in EMEs, but also provide a model where frictions in the supply of physical inputs—as opposed to frictions in the creation of customer capital—interact with firms' price-setting behavior and therefore inflation dynamics.

The rest of the paper is structured as follows. Section 2 describes the empirics. First, we present evidence on the relevance of trade credit for small and big firms in EMEs. Second, we describe the new dataset that we build and present our main empirical findings. Section 3 describes the model. Section 4 presents the results from a numerical experiment using the model that sheds light on the findings in Section 2. Section 5 concludes.

2   Price Dynamics and Firms' Financing Structure in the Data

2.1   The Importance of Trade Credit in EMEs

Existing evidence for AEs suggests that trade credit represents a non-negligible share of total assets and short-term credit, ranging from 18 to 25 percent of firms' total assets depending on the country (Guariglia and Mateut, 2006).[5] Despite this fact, access to commercial banks (including usage of credit cards and lines of credit) remains the primary source of external financing in these economies.[6] For example, data from Europe's Sur-

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search frictions.

[5] See Rajan and Zingales (1995) and Petersen and Rajan (1997) for early evidence on the importance of trade credit in the United States.

[6] The U.S. Joint Small Business Credit Survey Report (2014) notes that only 1 percent of surveyed firms report trade credit as being their primary source of (internal and external) funding. Even if we consider

vey on the Access to Finance of Enterprises (SAFE, 2015) suggests that among 28 EU economies, credit lines and commercial bank loans dominate as the main two sources of external financing, with trade credit considered a secondary source.[7]

Using data from the World Bank Enterprise Surveys, Allen *et al.* (2013) document that, while bank financing is important in both developed and developing countries, alternative sources of financing—including trade credit and leasing, both of which are relationship- and asset-based sources of financing—are more prevalent in developing countries. Table 1 confirms the importance of trade credit relative to bank credit in EMEs. In particular, while the bulk of investment is financed with bank credit in both EMEs and AEs, more than 50 percent of working capital is financed with trade credit in EMEs, compared to slightly more than one third in AEs.[8]

The Mexican central bank conducts a quarterly survey that evaluates the relative importance of different sources of credit among (formal) firms. Among those formal firms surveyed, 84 percent obtained external financing, 72 percent obtained resources from suppliers, and only 37 percent from banks. Figures 1a and 1b present this information, and importantly, they show that the relevance of supplier credit holds regardless of whether we consider smaller firms (Figure 1a) or larger firms (Figure 1b).[9]

2.2   Description of Data and Methodology

To document how firms' pricing behavior changes when they hold more trade credit in the form of account payables, we build a novel dataset using micro-level data from two sources: i) confidential goods-level consumer price data for Mexico's CPI, published by Mexico's

external financing alone, only 2 percent of firms report trade credit as their main external finance source (this stands in contrast to a combined 78 percent of firms reporting financial institutions–credit cards, lines of credit, or loans–as being their main source). Similarly, the Small Business Credit Survey (2015) reports that while 89 (30) percent of surveyed firms sought loans or lines of credit (credit cards) as sources of financing, only 9 percent sought trade credit.

[7] Indeed, close to 60 percent of firms in the survey ranked bank loans and credit lines as their primary source of external financing, while 47 percent cited leasing as their primary source. In contrast, only 33 percent of firms mentioned trade credit as a primary source of external resources (Organisation for Economic Co-operation and Development, 2015).

[8] External finance in Table 1 is defined as the sum of bank credit and trade credit from suppliers. These facts are consistent with Beck, Demirguc-Kunt and Maksimovic (2008). A caveat regarding Table 1 is in order: while the majority of firms in AEs are registered (and therefore considered formal), the opposite is true in EMEs. In turn, informal firms have little or no access to bank credit (or formal credit markets in general), and often turn to no-banking sources for external financing. Therefore, the differences in trade credit and alternative financing between EMEs and AEs are starker once we account for the prevalence of informal firms in EMEs. Table A.1 in the Appendix shows that alternative finance (which includes trade credit, leasing, informal sources, and resources from friends and family) represents roughly 50 percent of total external financing (comprised of market, bank, and alternative finance) among a comprehensive group of EMEs. This stands in contrast with AEs, where trade credit represents 35 percent of external finance.

[9] Evidence from previous years (1998-2009) confirms the importance of external resources from suppliers, even among large firms. We do not present this evidence below since it is based on an older version of the survey, which is not fully comparable with the methodology used in the new survey after 2009.

Tab. 1. Share of Working Capital and Investment Financed with Trade Credit as a Proportion of External Finance—Emerging and Advanced Economies

EMEs	Working K Fin. w. TC (% Ext. Fin.)	Investment Fin. w. TC (% Ext. Fin.)	AEs	Working K Fin. w. TC (% Ext. Fin.)	Investment Fin. w. TC (% Ext. Fin.)
Argentina	68.10	51.74	Germany	42.15	15.67
Chile	44.11	12.87	Greece	49.79	26.52
China	40.74	29.69	Hungary	57.96	17.55
Colombia	67.03	32.27	Ireland	28.66	4.124
Indonesia	50.99	22.42	Israel	22.79	4.242
Malaysia	35.02	24.88	Korea	2.817	0.498
Mexico	66.04	63.93	Portugal	38.96	5.844
Peru	50.71	23.90	Spain	44.52	15.18
Philippines	40.00	20.47	Sweden	46.63	6.977
Poland	63.75	43.98			
South Africa	75.85	13.13			
Turkey	27.93	4.848			
Mean EMEs	**52.52**	**28.68**	**Mean AEs**	**37.14**	**10.73**

Notes: Authors' calculations using World Bank Enterprise Surveys (year varies by country). External finance corresponds to the sum of credit from banks and trade credit from suppliers. Firms use internal resources in addition to external finance to finance their working capital expenditures and investment, where internal resources represent a substantial source of total (that is, external plus internal) financing. The country classification (emerging or advanced) is based on the definition used by the International Monetary Fund.

national statistical agency *Instituto Nacional de Estadística y Geografía* (INEGI), and ii) firm-level balance sheet data for firms in the Mexican stock exchange (that is, from publicly-traded firms) from Bloomberg.[10] The new dataset we construct allows us to create a price index by firm based on the products that make up the Mexican CPI and then link each price index to the corresponding firm's balance sheet information.

The CPI dataset has biweekly frequency starting from 2009Q3 until 2016Q4. The data allow us to create a firm-specific price index from 2009Q3 to 2016Q4 since our financial dataset is only available at a quarterly frequency. We cannot use price data prior to 2009Q3 because the product details are not listed. Moreover, we note a methodological change in both the homogeneous product categories "genéricos" we consider and weights used to calculate the index took place December 2010.[11] We circumvent this issue by considering

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[10] While the sample of publicly-traded firms in Mexico is small, it is the only sample that has high-frequency, time-series balance sheet information, where the latter is critical to explore how firms' financing structure affects price dynamics.

[11] Examples of specific homogeneous product categories include: cigarettes, beer, cell phone services,

Fig. 1. Percent of Firms Who Obtained External Financing (By Source)
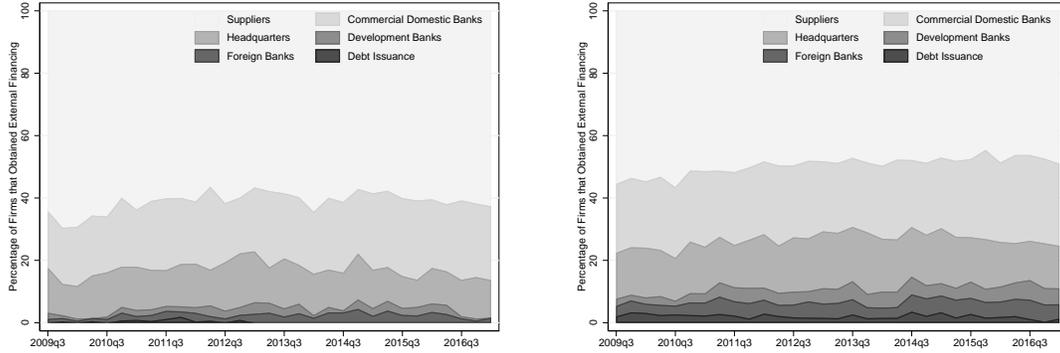
(a) Small and Medium Firms, < 100 Employees   (b) Large Firms, > 100 Employees

Source: Encuesta de Evaluación Coyuntural del Mercado Crediticio, Banco de México.

two separate datasets. The first dataset corresponds to the period 2009-2010 and the second to the period 2011-2017. We process the data for each sample separately given that the weights and the product categories differ. Ultimately, since we are interested in constructing an aggregate price index *per firm*, we merge the two datasets and consider the final weighted price per firm.

The first sample (years 2009-2010) is comprised of 84,365 products reported every two weeks, which are divided into 315 homogeneous product categories and sampled in 46 cities. The second sample (years 2011-2016) is comprised of 84,544 products reported every two weeks, which are divided into 283 product categories and sampled in 46 cities.

Each sample has a weight assigned per generic-city. All the products corresponding to the same generic category and surveyed in the same city share this weight. These weights sum to one and are computed from Mexico's household income and expenditures survey, *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH Survey), from 2008 to 2010. INEGI uses this survey to create a representative consumer basket for the Mexican population. From these weights, we proceed to assign a biweekly weight to each product depending on the number of generic-city products per fortnight. We describe how we use this weight per product to create weights per firm below. Additionally, we create a dataset where we include all the brands corresponding to each private non-financial firm listed in the Mexican stock market. This allows us to identify the firms that can be matched with specific products in the CPI. For example, firms in the mining and construction sectors cannot easily be matched with products in the consumer basket given the nature of the sectors. Then, identifying the brands owned by each firm allows us to homogenize the products' specification and to create the corresponding weights per firm.

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tennis shoes, men's pants, etc.

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In order to create the price index by listed firm, we use the variable named "Especificación" to match each product with the corresponding firm. This variable has information regarding the product listed in the index. In particular, the variable includes the commercial name of the product, the specifics of the product's presentation (for example, its weight), and the quantities. There are many product categories that do not assign a brand to the product ("S/M" or "NULL"), or others such as private or public services that do not have a specific brand.

To start analyzing the data, we first use the information in the variable named "Clave," which allows us to identify each product individually. The variable is a numeric code that includes information regarding the place where it was measured, the generic number of the product, and a specific identification number. First, we create a weight per product per fortnight, taking into account the weight per generic-city. We create a variable including just the digits that correspond to the generic and we drop all the product categories that do not provide information on the firms listed in the stock market as well as firms that are state-owned. In this same step, we also drop product categories that include food sold in bulk, services such as electricity, movie theaters, schools, and so on, as these products are not informative for our purposes. On average, these non-informative products correspond to 44 percent of the goods in the consumer basket (0.73 in weights). All told, we are able to analyze the brands of the remaining 56 percent of the sample (0.27 in weights). The above details are summarize in Table 2.

Tab. 2. Total and Sample After Dropping Non-Informative Product Categories and Product Information

	2009-2010	2011-2016
Sample to total products	46,492/84,365	48,147/84,544
Sample to total product categories	213/315	186/283
Weight relative to total CPI	0.271	0.273
Products that change firm up to four times	46,471	43,256
Other products	21	4,891

Source: Authors' calculations using data from INEGI.

The second step is to "clean" the variable "Especificación" to be able to match it with our sample of publicly-listed firms. One of the main issues with this variable is that it depends on who reports the data and therefore it is not systematically consistent. For example, the product *Coca-Cola* appears as *Coca*, *Coca Cola*, or *Coca-Cola*, even though all three represent the same product. To deal with this issue, we go through the descriptions of the products individually and homogenize them to the extent possible.

Then, we merge the relative prices (variable "Relativo Q_i", where subscript i refers to the biweekly observation of the price index with respect to the last two weeks of December

2010) of all the commercial products from the same firm. Thus, using the previous example of *Coca-Cola*, we bundle together *Coca-Cola*, *Sprite*, *Fanta*, etc. In general, product specifications change over the time. If the commercial name belongs to the same listed firm, we keep the relative price for that firm. However, if there is a change of firm, we break the time series and assign the data accordingly. We only keep the products that change firms up to four times and that represent over 90 percent of the products with an assigned brand in the CPI. This is relevant because, in general, the products that change more times correspond to clothing products, which cannot be matched with publicly-listed firms.

2.3 Econometric Analysis and Empirical Results

2.3.1 Firm Characteristics and Firm Categories: Some Facts

To explore how firms' financing structure—which includes trade credit usage as reflected in account payables as well as bank credit—and price setting may be related, we match our price index dataset with data on the balance sheet of publicly-traded firms obtained from Bloomberg. We only consider listed firms that have matched products in our consumer price index dataset. This implies that we exclude wholesale firms, commodity producers, and state-owned firms, among others. Thus, we are mainly left with retailers and manufacturers.

Inflation in Firm Sample vs. Aggregate Inflation in Mexico   While we restrict our firm sample to publicly-traded firms in order to exploit the availability of balance sheet information on these firms, Table 3 summarizes the main characteristics of our sample and compares them to the CPI data. Additionally, Figure B.1 in the Appendix shows that the CPI series we create using our firm sample tracks the behavior of the general CPI and the food-based CPI in Mexico well. Thus, despite our restricted firm sample, understanding the behavior of price dynamics among publicly-traded firms can shed light on economy-wide price dynamics.

To analyze how firms' trade credit usage may influence their price-setting behavior, we classify firms into two categories based on their trade credit-to-bank credit ratio. We sort firms into "low" and "high" trade-to-bank credit ratio categories based on whether a given firm's trade-to-credit ratio is below or above the median in that period (Table 3 already shows this classification). Of note, Figure B.3 in the Appendix shows that most of the firms remain in the same category for the entirety of the sample period, and only a small number of firms change categories between 2009 and 2016.

Fact 1 As shown in panels A and B of Figure B.7, *firms categorized as having a high trade-to-bank credit ratio tend to be those with more employees and higher total sales* over

Tab. 3. Summary Statistics of Relative Price Characteristics

	CPI	Food-CPI	Sample	High T-BC	Low T-BC
Inflation	0.0096	0.0019	0.0090	0.0024	0.0104
	(0.0084)	(0.0076)	(0.0068)	(0.0285)	(0.0085)
Trade-to-Bank Credit (T-BC)			0.9916	1.7652	0.2240
			(0.3445)	(0.6884)	(0.0248)
N. of firms			39	15.9032	15.2903
				(2.8908)	(2.7591)

Source: Authors' calculations using data from INEGI and Bloomberg.

most of the sample.[12] When looking at the growth rates of trade credit and bank credit separately, the growth rate of trade credit in both firm categories is similar, while low trade-to-bank credit ratio firms tend to exhibit higher growth rates in bank credit (see Figure B.5).

Fact 2   Figure B.4 plots the dynamic behavior of inflation over our sample period (2009Q3-2016Q4). Two facts stand out. First, the dynamics of category-specific inflation do not look all that different across firm categories. However, the mean of the high trade-to-bank credit ratio firms is lower than the one with in low-ratio firms. Second, the standard deviation of firms with a high trade-to-bank credit ratio is larger, implying that these firms tend to change their prices more than firms with a lower trade-to-bank credit ratio. This information also appears in Table 3.

2.3.2 Empirical Specification and Main Results

To formally show how the financing structure of firms affects price dynamics, we follow related literature and estimate a linear pricing regression of the form

$$\pi_{i,t}^q = \beta' \mathbf{X_{i,t}} + \gamma \mathbf{Z_t} + \omega + \varepsilon + u_{i,t}, \tag{1}$$

where $\pi_{i,t}^q$ is the quarterly inflation rate of firm i ($\pi_{i,t}^q = \log p_{i,t}^q - \log p_{i,t-1}^q$). The firm-level independent variables vector, $\mathbf{X_{i,t}}$, includes the trade-to-bank credit ratio, the bank credit-to-liabilities ratio, the inventories-to-sales ratio, the liquidity ratio and the growth rates of trade credit, bank credit, and cash holdings. We also control for (sectoral and not firm-specific) labor productivity in the sector to which any given firm belongs. Moreover, to control for economy-wide (macro) trends that may affect inflation dynamics, $\mathbf{Z_t}$ includes the changes in the real exchange rate and in the real interest rate, respectively. We include firm- and time- fixed effects, ω and ε, respectively. It is important to notice that we only

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[12] However, having higher total assets does not necessarily coincide with having a higher trade-to-bank credit ratio.

look at the liability side of the firms, i.e., accounts payable and not accounts receivable, so we think of listed firms as receiving credit from their suppliers, as shown in the survey in Section 2.1.

Table 4 summarizes the results. Columns (1) to (3) show the results with the macro-variable controls, while columns (4) to (6) specify the regression results by excluding both the macro variables and the growth rates for cash or bank credit as controls. Columns (1) and (4) include the full firm sample (both high and low trade-to-bank-credit ratio firms); the rest of the columns show the results for low trade-to-bank credit ratio firms (columns (2) and (5)), and high trade-to-bank credit ratio firms (columns (3) and (6)). According to columns (1), (3), (4), and (6), i.e., all firms and the high trade-to-bank credit firms, differences in trade credit growth imply significant differences in firms' inflation rates. In particular, all else equal, higher trade credit growth brings prices down by roughly 1 to 2 percentage points depending on whether we look at the complete sample or only at the high trade-to-bank credit ratio firms. One way to rationalize this result may be that firms with a high trade-to-bank credit ratio have cheaper access to resources, which gives these firms the flexibility to decrease prices relative to firms with a low trade-to-bank credit ratio.[13] Additionally, bank-credit growth does not explain variation in inflation in any of the specifications.

Finally, we note that the specifications that control for economy-wide factors have the expected signs. More important, though, is the fact that even after controlling for these and other factors, trade credit growth appears to play a non-negligible role in affecting inflation. In what follows, we use a simple model to shed light on these results.

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[13] We also note that, for firms with a low trade-to-bank credit ratio, the inventories-to-sales ratio is statistically significant. One reason this may be the case is that greater accumulation of inventories increases inventory costs and puts firms into a more difficult financial position, which prompts an increase in prices by those firms to partially offset the rise in inventory-holdings costs.

Tab. 4. Balance Sheet Components as Explanatory Variables for Firm Inflation, High vs. Low Trade-to-Bank Credit Ratio Firms, 2009Q3-2016Q4

	(1) C. Sample	(2) Low T-BC	(3) High T-BC	(4) C. Sample	(5) Low T-BC	(6) High T-BC
$\frac{\text{Trade Cr.}}{\text{Bank Cr.}}$	-0.0033 (0.00313)	-0.029 (0.0363)	-0.0037 (0.00477)	-0.0011 (0.00282)	-0.0375 (0.0347)	-0.0008 (0.00417)
$\log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-0.0103** (0.00517)	-0.0043 (0.00686)	-0.0176** (0.00845)	-0.0084* (0.00497)	0.0012 (0.00619)	-0.0191** (0.00829)
$\log\left(\frac{\text{Cash}_t}{\text{Cash}_{t-1}}\right)$	-0.0014 (0.00179)	0.0018 (0.00210)	-0.0009 (0.00280)			
$\log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-0.0022 (0.00502)	-0.00426 (0.00529)	-0.0006 (0.00833)			
$\frac{\text{Bank Cr.}}{\text{Tot. Liab.}}$	-0.0074 (0.0215)	-0.0289 (0.0259)	0.0060 (0.0401)	-0.0004 (0.0203)	-0.0313 (0.0255)	0.0115 (0.0367)
$\frac{\text{Cash+Short T.Borr.}}{\text{Assets}}$	0.0168 (0.0218)	0.0081 (0.0220)	-0.0050 (0.0461)	0.015 (0.0204)	0.0176 (0.0203)	-0.0024 (0.0415)
$\frac{\text{Inventories}}{\text{Sales}}$	-0.0003 (0.0106)	0.0225* (0.0126)	-0.0187 (0.0185)	-0.0001 (0.00122)	0.0210* (0.0123)	0.0003 (0.00142)
Sec. Productivity	-0.165** (0.0641)	-0.0746 (0.0729)	-0.286*** (0.110)			
Cat. $\frac{\text{Trade Cr.}}{\text{Bank Cr.}}$	-0.0009 (0.00461)			-0.0016 (0.00456)		
$\log\left(\frac{R_t^{mon.\ pol.}}{R_{t-1}^{mon.\ pol.}}\right)$	-0.571*** (0.155)	0.238* (0.142)	-2.844*** (0.332)			
$\log\left(\frac{rer_t}{rer_{t-1}}\right)$	1.141*** (0.244)	-0.0409 (0.221)	4.690*** (0.524)			
Constant	-0.0448** (0.0180)	-0.0038 (0.0249)	-0.188*** (0.0301)	-0.0001 (0.0140)	-0.0017 (0.0225)	0.0120 (0.0193)
Observations	739	376	363	768	390	378
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

$^*p < 0.1,\ ^{**}p < 0.05,\ ^{***}p < 0.01$

Notes: The dependent variable in all columns is the firm's quarterly inflation rate $\pi_{i,t}^q$. The columns (1) and (4) include all firms in our sample. Columns (2) and (5) only include firms with low trade-to-bank credit. Columns (3) and (6) correspond to the results for firms with a high trade-to-bank credit ratio. Standard errors are reported in parentheses.

3 The Model

We present a baseline economy with a single sector to highlight the main features of the model. Appendix G presents a richer environment with sectoral heterogeneity in price-setting that allows us to delve deeper into the factors that may explain the sectoral facts in Section 2. We discuss the findings in that model as part of our quantitative experiments.

The baseline economy is comprised of perfectly-competitive physical input suppliers, perfectly-competitive intermediate goods firms, monopolistically-competitive final goods firms, and households. Households own all firms. Physical input suppliers accumulate physical inputs and supply them to intermediate goods firms via trade-credit relationships, where the latter are rooted in search frictions.[14] Intermediate goods firms use these physical inputs along with household-supplied labor to produce inputs for final goods firms. To introduce a tractable notion of bank credit, we assume that a fraction of intermediate goods firms face a working capital constraint such that firms' wage bill must be financed in advance with bank credit.[15] Additionally, final goods firms use inputs from intermediate-goods firms to produce final goods. Following the New Keynesian literature, firms that choose their prices face price stickiness *à la* Calvo. Given our focus on the structure of input markets, we assume a closed economy.[16]

Obtaining physical inputs requires searching for input suppliers and creating long-term relationships that support a stable stream of (possibly specialized) inputs for production. Then, given that trade credit is relationship-based, search frictions in input markets are a natural way to capture interfirm trade credit.[17]

3.1 Households

A representative household chooses consumption, c_t, labor supply, n_t, and real deposits, d_t, to maximize $E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, n_t)$ subject to

$$c_t + d_t = \frac{R_{t-1}}{\pi_t} d_{t-1} + w_t n_t + \Pi_{x,t} + \Pi_{m,t} + \Pi_{y,t},$$

where R_{t-1} is the gross nominal interest rate and the gross inflation rate is $\pi_t = p_t/p_{t-1}$. $\Pi_{x,t}, \Pi_{m,t}$, and $\Pi_{y,t}$ denote profits from physical input producers, intermediate goods firms,

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[14] We do not take a specific stand on the nature of physical inputs. These can range anywhere from physical capital such as machinery and equipment, to perishable and non-perishable goods used in the production of specific foods in the consumer basket and to specific inputs for the production of garments, for example. What ultimately matters is that the market for such inputs is frictional given that production firms must search for (reliable) input suppliers.

[15] Allowing for financial frictions as in, say, Bernanke, Gertler and Gilchrist (1999) or others, does not change our findings.

[16] Assuming a small open economy does not alter the main mechanisms in the model; we present the results in Appendix H.

[17] See Burkart and Ellingsen (2004) and Cuñat (2007) for more on trade credit.

and final goods firms, respectively. The first-order conditions yield a standard labor supply condition

$$u_{c,t}w_t = u_{n,t}, \tag{2}$$

and an Euler equation over deposits:

$$u_{c,t} = E_t\beta\left[\frac{R_t u_{c,t+1}}{\pi_{t+1}}\right]. \tag{3}$$

The stochastic discount factor is given by $\Xi_{t|0} = \beta^t u_{c,t}/u_{c,0}$.

3.2 Matching Preliminaries

We follow the general setup in Kurmann and Petrosky-Nadeau (2007) and Arseneau, Chugh and Kurmann (2008), who are the first to introduce search frictions in physical capital markets in a general equilibrium environment, and model the supply and demand for physical inputs x_t as a process rooted in search frictions.[18] More specifically, let $m(\omega_t, s_t)$ be a constant-returns-to-scale matching function that combines available physical inputs ω_t supplied by physical input suppliers and search resources s_t from intermediate goods firms in order to produce new (productive) matches in physical input markets. Then, the matching probability from the perspective of physical input suppliers is $q(\theta_t) = m(\omega_t, s_t)/\omega_t$ and the matching probability from the perspective of intermediate goods firms is $f(\theta_t) = m(\omega_t, s_t)/s_t$, where market tightness is defined as $\theta_t \equiv \omega_t/s_t$.

3.3 Physical Input Suppliers and Trade Credit

Physical input suppliers accumulate new physical inputs ω_t each period to match them with intermediate goods firms. Specifically, they choose the supply of *new* physical inputs ω_t and the desired amount of physical inputs they would like to have matched (and be productive) next period x_{t+1} to maximize $E_0\sum_{t=0}^{\infty}\Xi_{t|0}\Pi_{x,t}$ subject to

$$\Pi_{x,t} = r_{x,t}x_t + [1 - q(\theta_{t-1})]\omega_{t-1} - \omega_t + \rho x_t, \tag{4}$$

and the perceived evolution of physical inputs

$$x_{t+1} = (1 - \rho)x_t + \omega_t q(\theta_t), \tag{5}$$

where $r_{x,t}$ is the real price of physical inputs (determined via bilateral Nash bargaining), $q(\theta_t)$ is the matching probability from the input supplier's perspective and θ_t is market tightness in physical input markets, and ρ is the exogenous separation probability at the end of each period. The expression for producer profits $\Pi_{x,t}$ shows that both unmatched

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[18] We discuss the role of search frictions as part of our quantitative experiments. See Kurmann (2014) for a theoretical approach to search frictions in capital markets and the holdup problem.

new physical inputs, $[1-q(\theta_{t-1})]\omega_{t-1}$, and separated physical inputs, ρx_t, represent revenue for these suppliers. *Of note, x_t represents the amount of matched (and active) physical inputs in period t, which we interpret as the existing stock of trade credit.*

First-order conditions yield a physical input supply condition:

$$\frac{1 - E_t\Xi_{t+1|t}\left[1 - q(\theta_t)\right]}{q(\theta_t)} = E_t\Xi_{t+1|t}\left\{r_{x,t+1} + \rho + (1-\rho)\frac{1 - E_t\Xi_{t+2|t+1}\left[1 - q(\theta_{t+1})\right]}{q(\theta_{t+1})}\right\}. \tag{6}$$

Intuitively, this expression equates the expected marginal cost of supplying a unit of physical inputs to intermediate goods firms—given by the value of a matched unit of inputs net of the revenue the supplier would have if she were to keep these inputs instead of matching them, all adjusted by the matching probability—to the expected marginal benefit of supplying a unit of physical inputs—given by the price of those inputs, the value of any separated inputs from existing input credit relationships that become defunct in period $t+1$, and the continuation value of these relationships if they survive into the next period.

3.4 Intermediate Goods Firms

Perfectly-competitive intermediate goods firms use labor, n_t, and (trade-credit-based) physical inputs, x_t, to produce according to a standard constant-returns-to-scale production function $F(n_t, x_t)$ where, as noted earlier, obtaining physical inputs is subject to search frictions.[19] Firms choose labor demand, n_t, the desired amount of physical inputs, x_{t+1}, and the amount of resources devoted to searching for physical inputs, s_t, to maximize $E_0\sum_{t=0}^{\infty}\Xi_{t|0}\Pi_{m,t}$ subject to

$$\Pi_{m,t} = mc_t z_t F(n_t, x_t) - w_t\left(1 - \phi_n + \phi_n E_t\Xi_{t+1|t}R_t\right)n_t - r_{x,t}x_t - \kappa\left(s_t\right),$$

and the perceived evolution of physical inputs

$$x_{t+1} = (1-\rho)x_t + s_t f(\theta_t), \tag{7}$$

where mc_t is the *real* price of intermediate goods, w_t is the real wage, $0 < \phi_n \leq 1$ is the fraction of the wage bill financed with bank credit, $\kappa\left(s_t\right)$ is the resource cost of search where $\kappa'\left(s_t\right) > 0$ and $\kappa''\left(s_t\right) \geq 0$, and $f(\theta_t)$ is the matching probability from the perspective of intermediate goods firms. We define real bank credit $b_t = \phi_n w_t n_t$. Then, the *trade-to-bank credit ratio* is given by $\Phi_t \equiv x_t/b_t$ and *(gross) trade credit growth* by $\Omega_t \equiv x_t/x_{t-1}$.[20]

First-order conditions yield a standard labor demand condition adjusted for the presence of a working capital constraint

$$mc_t z_t F_n(n_t, x_t) = w_t\left(1 - \phi_n + \phi_n E_t\Xi_{t+1|t}R_t\right), \tag{8}$$

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[19] Appendix E shows that introducing physical capital via frictionless markets on top of trade-credit-based physical inputs does not change any of our main conclusions and, in fact, makes our results even stronger.

[20] Defining the trade-to-bank credit ratio as $r_{x,t}x_t/b_t$ does not change our results.

and a physical input demand condition

$$\frac{\kappa'(s_t)}{f(\theta_t)} = E_t \Xi_{t+1|t} \left\{ mc_{t+1}z_{t+1}F_x(n_{t+1}, x_{t+1}) - r_{x,t+1} + (1-\rho) \left[\frac{\kappa'(s_{t+1})}{f(\theta_{t+1})} \right] \right\}. \qquad (9)$$

Intuitively, firms equate the marginal benefit of having one more unit of labor to the marginal cost, where the latter is affected by the cost of bank credit. In turn, firms equate the expected marginal cost of searching for physical input producers—that is, the marginal cost in terms of physical resources $\kappa'(s_t)$ adjusted by the probability that a match materializes—to the expected marginal benefit of doing so. The latter is given by the expected marginal product of physical inputs net of the cost of such inputs as well as the continuation value of trade credit relationships.

3.5 Price Determination in Physical Input Markets

Let $\mathbf{W}_t$ and $\mathbf{J}_t$ be the values of having a matched unit of physical inputs for intermediate goods firms and physical input suppliers, respectively. In particular, one can show that

$$\mathbf{W}_t = mc_t z_t F_x(n_t, x_t) - r_{x,t} + (1-\rho)E_t \Xi_{t+1|t} \mathbf{W}_{t+1},$$

and

$$\mathbf{J}_t = r_{x,t} + \rho + (1-\rho)E_t \Xi_{t+1|t} \mathbf{J}_{t+1}.$$

Assuming that physical input suppliers' reservation value of not matching a unit of physical inputs with intermediate goods firms is simply the value of that unused input (that is, 1), the solution to the bilateral Nash bargaining problem between physical capital producers and intermediate goods firms yields a standard implicit function for the real price of physical inputs $r_{x,t}$:

$$\mathbf{W}_t = \left(\frac{\eta}{1-\eta} \right) (\mathbf{J}_t - 1), \qquad (10)$$

where $0 < \eta < 1$ is the bargaining power of intermediate goods firms and $(\mathbf{J}_t - 1)$ represents input suppliers' net value of a matched unit of physical inputs.[21] Using the expressions above, one can show that the real price $r_{x,t}$ is

$$r_{x,t} = \eta \left[mc_t z_t F_x(n_t, x_t) + (1-\rho) \frac{\kappa'(s_t)}{f(\theta_t)} \right] + (1-\eta)\rho. \qquad (11)$$

This expression is similar to the one in Arseneau *et al.* (2008). Intuitively, the Nash price of physical inputs is a convex combination of those inputs' marginal product and the expected (marginal) cost of searching for those inputs and suppliers' outside option. Importantly, all else equal, a fall in the market tightness, θ, puts downward pressure on the Nash price.

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[21] Allowing for physical depreciation of inputs does not change any of our results (this could easily be incorporated into the value of ρ).

3.6 Final Goods Firms

Monopolistically-competitive final goods firms purchase intermediate goods from intermediate goods firms at real price mc_t. Each period, firms face an exogenous probability of not being able to change prices $0 < \phi < 1$. They choose their relative price $p_t(i)$ to maximize

$$E_0 \sum_{j=0}^{\infty} (\beta\phi)^j \Lambda_{j,t} \frac{p_t}{p_{t+j}} \left[p_{t+j}(i) y_{t+j}(i) - p_{t+j} mc_{t+j} y_{t+j}(i) \right]$$

subject to the demand function $y_t(i) = [p_t(i)/p_t]^{-\varepsilon} y_t$, where total final output $y_t = \left[\int_0^1 y_t(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}}$, the aggregate price level $p_t = \left[\int_0^1 p_t(i)^{1-\varepsilon} di \right]^{\frac{1}{1-\varepsilon}}$, ε is the elasticity of substitution between goods, and $\Lambda_{j,t} \equiv u_{c,j}/u_{c,t}$. The optimal price (after imposing symmetry), p_t^*, is standard and can be expressed as

$$p_t^* = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \frac{g_{1t}}{g_{2t}}, \tag{12}$$

where

$$g_{1,t} = u_{c,t} y_t mc_t p_t^{\varepsilon} + \beta E_t \phi \left(\frac{\pi_{t+1}}{\pi} \right)^{\varepsilon} g_{1,t+1}, \tag{13}$$

and

$$g_{2j,t} = u_{c,t} y_t p_t^{\varepsilon} + \beta E_t \phi \left(\frac{\pi_{t+1}}{\pi} \right)^{\varepsilon-1} g_{2,t+1}. \tag{14}$$

It is easy to show that the price index evolves as follows:

$$p_t^{1-\varepsilon} = \phi \left(\frac{p_{t-1}}{\pi_t} \right)^{1-\varepsilon} + (1 - \phi) (p_t^*)^{1-\varepsilon}. \tag{15}$$

Finally, we can define price dispersion ξ_t in a recursive way as $\xi_t = (1 - \phi) (p_t^*)^{-\varepsilon} + \phi (\pi_t)^{\varepsilon} \xi_{t-1}$. Then, total production $Y_t = \xi_t y_t$.

3.7 Monetary Policy

The central bank follows a standard Taylor rule with smoothing parameter ρ_r

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\rho_r} \left[\left(\frac{Y_t}{Y} \right)^{\phi_y} \left(\frac{\pi_t}{\pi} \right)^{\phi_\pi} \right]^{1-\rho_r} \exp(\varepsilon_{r,t}), \tag{16}$$

where $0 \leq \rho_r < 1$, $\phi_y \geq 0$ and $\phi_\pi > 1$, $\varepsilon_{r,t}$ is an i.i.d. shock, and variables without subscripts denote variables in steady state.

3.8 Resource Constraint

The economy's resource constraint is given by

$$Y_t = c_t + \omega_t - [1 - q(\theta_{t-1})]\,\omega_{t-1} + \kappa(s_t) - \rho x_t, \tag{17}$$

where $\omega_t - [1 - q(\theta_{t-1})]\,\omega_{t-1}$ represents net investment in physical inputs, $\kappa(s_t)$ is a resource cost. Also, recall that total production is affected by price dispersion as a result of price stickiness (that is, $Y_t = \xi_t y_t$).

4 Numerical Experiments

To shed light on the structural characteristics of firms and economic mechanisms that (qualitatively) rationalize the empirical findings in Section 2, we perform a series of numerical experiments in a calibrated version of the model. Importantly, the primary role of our model is to provide a tractable and transparent environment in which we can better understand the connection between trade credit and price dynamics in the data, rather than to *quantitatively* match the stylized facts in Section 2. Indeed, quantitatively matching the empirical facts would require a medium-scale model with a rich shock specification that includes both domestic and foreign shocks, as well as a more complex firm and financial structure, both of which would cloud the key economic mechanisms that may be at play.[22]

4.1 Parameterization

4.1.1 Functional Forms

The functional forms are standard in the business cycle literature. The utility function is $u(c_t, n_t) = \left[c_t^{1-\sigma}/(1-\sigma) - \psi_n n_t^{1+\gamma_n}/(1+\gamma_n) \right]$, where $\sigma > 0$ is the coefficient of relative risk aversion, $\psi_n > 0$ is the relative weight of labor in the utility function, and $\gamma_n > 0$ is the inverse of the Frisch elasticity of labor supply. The production function for intermediate goods firms is Cobb-Douglas $F(n_t, x_t) = n_t^{1-\alpha} x_t^{\alpha}$, where $0 < \alpha < 1$ is the share of trade credit in the production. The matching function is constant-returns-to-scale and follows the functional form in Den Haan, Ramey, and Watson (2000): $m(\omega_t, s_t) = \omega_t s_t / (\omega_t^{\mu} + s_t^{\mu})^{1/\mu}$ where $\mu > 0$ is the matching elasticity.[23] The total cost of searching is given by $\kappa(s_t) = \psi_s(s_t)^{\eta_s}$, where $\psi_s > 0$ is a scale parameter and $\eta_s \geq 1$ is the elasticity of seach cost. Finally, aggregate productivity shocks follow a standard AR(1) process in logs: $\ln(z_t) = (1 - \rho_z)\ln(z) + \rho_z \ln(z_{t-1}) + \varepsilon_t^z$, where $\varepsilon_t^z \sim N(0, \sigma_z)$.

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[22] Moreover, this richer environment would be more suitable for a paper that focuses explicitly on the role of monetary policy, which our paper does not address, and not for a paper that focuses on a positive analysis of firms' financing structure and price dynamics.

[23] In contrast to a Cobb-Douglas specification, this functional form guarantees that both matching probabilities are bounded between 0 and 1.

4.1.2 Parameter Values

We show the baseline calibration of the model in Table 5. We adopt standard values for the parameters that are commonly used in the business cycle literature: a subjective discount factor $\beta = 0.985$, a relative risk aversion parameter $\sigma = 2$, an elasticity of substitution between final goods $\varepsilon = 11$, and an inverse Frisch elasticity of labor supply $\gamma_n = 1$. Without loss of generality, we normalize aggregate productivity $z = 1$, set the persistence of productivity shocks $\rho_z = 0.95$, and the size of the shock $\sigma_z = 0.01$. Also, following the New Keynesian literature, we consider a zero net-inflation steady state, so that $\pi = 1$. We initially set $\mu = \eta = 0.5$, $\rho = 0.025$, $\phi_n = 1$ (implying that all the wage bill is financed with bank credit) and $\eta_s = 1$ (implying linear search costs) and experiment with alternative values as part of our robustness checks (see Appendix F). We estimate a standard Taylor rule for Mexico and set $\phi_y = 0.5365$, $\phi_\pi = 1.678$, $\rho_r = 0.70$, consistent with existing studies for Mexico.[24] For illustrative purposes, the monetary policy shock is $\sigma_r = 0.01$. Following the New Keynesian literature, we set $\phi = 0.75$, implying that prices change on average every three quarters.

We calibrate the remaining parameters ψ_n, ψ_s, and α so that steady-state hours worked are 0.33, the total cost of searching for physical input producers is roughly 1 percent of output, and the steady-state trade-to-bank credit ratio Φ is 0.23, where this target corresponds to the ratio for *low* trade credit-to-bank credit firms in our sample. All told, this yields $\psi_n = 26.4658$, $\psi_s = 1.6594$, and $\alpha = 0.0386$.

4.2 Main Results

Our first experiment consists of simulating the model and considering the correlation between trade credit growth and inflation amid aggregate productivity and monetary policy shocks under two calibrated economies.[25] In what follows, we refer to a rise in nominal interest rates (aggregate productivity) as a positive monetary policy (aggregate productivity) shock.

The first economy is based on our baseline calibration with a low steady-state trade-to-bank credit ratio of 0.23. The second economy is based on the same economy with a steady-state high trade-to-bank credit ratio of 0.83, which corresponds to the ratio for *high* trade credit-to-bank credit firms in our sample. To achieve this, we change α while keeping all other calibrated parameters at their baseline values. This allows us to explore how the average (steady state) trade-to-bank credit ratio in the economy affects price dynamics amid aggregate productivity and monetary policy shocks.

Figures 2a and 2b show that, *relative to a baseline economy with a low steady-state trade-to-bank credit ratio*, an economy with a high steady-state trade-to-bank credit ratio exhibits a stronger negative correlation between trade-credit growth and inflation. This

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[24] The Taylor rule is estimated for the period 2005Q4 through 2017Q1.

[25] We simulate the model for 739 periods, which corresponds to our full time frame-firm sample.

Tab. 5. Parameters in Baseline Model

Parameter		Value	Source or Target
Preferences, technology, search & policy parameters			
β	Subjective discount factor	0.985	DSGE literature
σ	Coefficient of relative risk aversion	2	DSGE literature
γ_n	Inverse of Frisch elasticisticy of labor supply	1	DSGE literature
ψ_n	Labor weight on the ut. function	26.4658	Match ave. hours worked
ε	Elasticity of substitution between final goods	11	NK literature
α	Share of trade credit in the prd. function	0.0386	Calibrated to low T-BC ratio
μ	Matching elasticity	0.50	Baseline assumption
η	Bargain power of intermediate goods firms	0.50	Baseline assumption
ρ	Probability of separation	0.025	Baseline assumption
ϕ_n	Wage bill share financed with bank credit	1	Baseline assumption
η_s	Search cost elasticity	1	Linear search costs
ψ_s	Search cost scaling	1.6594	Search costs to 1% of output
ϕ	Calvo price stickiness	0.75	NK literature
π	Inflation in the deterministic steady state	1	NK literature
ϕ_y	Taylor rule parameter on output	0.5365	Estimated for Mexico
ϕ_π	Taylor rule parameter on inflation	1.678	Estimated for Mexico
ρ_r	Taylor rule persistence parameter	0.7	Estimated for Mexico
Shocks			
z	Steady-state aggregate productivity	1	Normalization
ρ_z	Persistence of productivity shock	0.95	DSGE literature
σ_z	Std. dev. of productivity shock	0.01	Baseline assumption
σ_r	Std. dev. of monetary policy shock	0.01	Baseline assumption

is broadly and qualitatively consistent with the empirical evidence in columns (2) and (3) in Table 4, where trade credit growth and inflation are negatively correlated but statistically *in*significant for *low* trade-to-bank credit ratio firms, and more strongly negatively correlated *and* statistically significant for *high* credit-bank credit ratio firms (in turn, the latter firms drive the negative (and statistically significant) correlation between trade credit growth and inflation in the whole firm sample).

In turn, 3a and 3b show the correlation between inflation and bank credit growth for the two economies (high- and low- ratio). The fact that under both economies the correlation is virtually zero is broadly consistent with the empirical results in Table 4, which suggest that bank credit growth has no significant effect on inflation, regardless of firm category. All told, these figures suggest that a simple model can successfully capture the qualitative patterns in the data beyond the link between trade credit growth and inflation.

Table 6 compares the unconditional correlations for two relevant variables—trade credit growth and bank credit growth—with inflation, both for the full firm sample and by

Fig. 2. Simulated Time Series: Inflation and Trade Credit Growth, Low and High Trade-to-Bank-Credit Ratio Economy
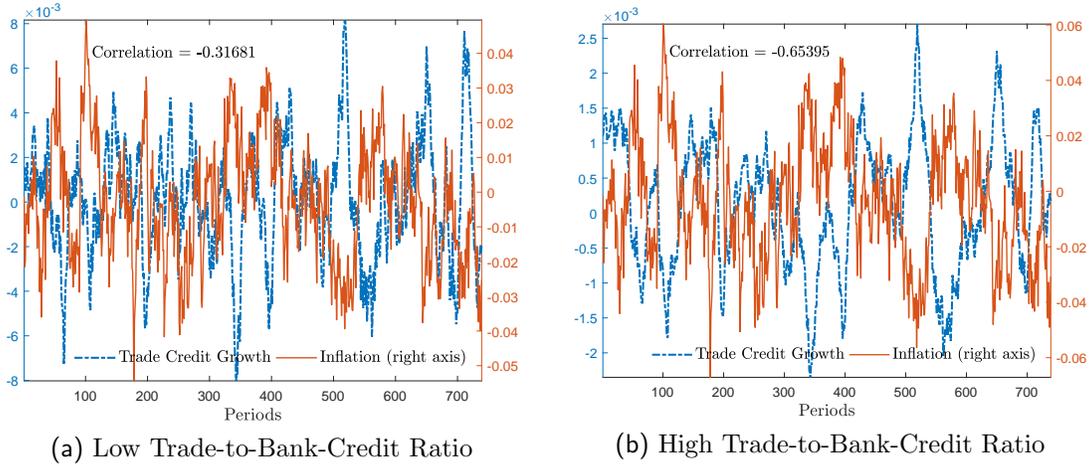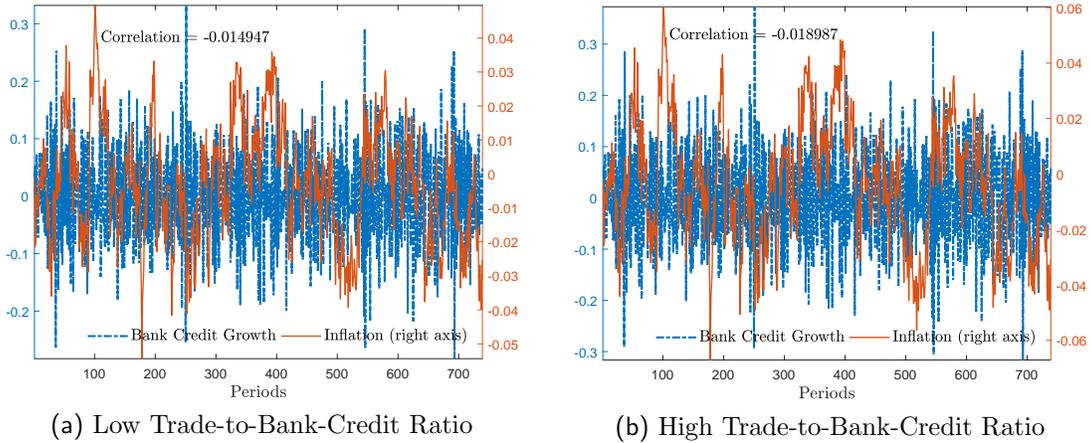

(a) Low Trade-to-Bank-Credit Ratio

(b) High Trade-to-Bank-Credit Ratio

Fig. 3. Simulated Time Series: Inflation and Bank Credit Growth, Low and High Trade-to-Bank-Credit Ratio Economy

(a) Low Trade-to-Bank-Credit Ratio

(b) High Trade-to-Bank-Credit Ratio

firm category (high-trade-credit-ratio and low-trade-credit-ratio firms) in the data to their model counterparts. For completeness, we include the results from our baseline model and the results from the two-sector model (whose details are discussed in Appendix G). While the one-sector baseline model can *qualitatively* generate the unconditional patterns in the data, the two-sector model does surprisingly well in capturing the fact that i) the relationship between inflation and trade credit growth in the complete firm sample is driven by high trade-to-bank-credit ratio firms, ii) that relation is negative for the high trade-to-bank

Tab. 6. Unconditional Correlation of Inflation with Trade Credit Growth, Bank Credit Growth, and the Trade-Bank Credit Ratio, 2009Q3-2016Q4

Correlations	(1) Aggregate	(2) Low T-BC	(3) High T-BC
Data			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-0.0617*	0.0250	-0.1037**
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-0.0073	-0.0480	0.0084
One-Sector Model			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	-0.3168	-0.6540
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	-0.0150	-0.0190
Two-Sector Model			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-0.0629	-0.0022	-0.1820
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-0.0047	-0.0021	-0.0075

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Notes: Column (1) includes all firms in our sample, column (2) only includes firms with low trade-to-bank credit, and column (3) corresponds to the results for firms with a high trade-to-bank credit ratio.

credit ratio firms, and insignificantly different from zero for the low trade-to-bank credit firm, and iii) the correlation of inflation with bank credit growth is virtually zero, both in the complete firm sample and in each firm category. These three findings are key elements present in our model.

Figure 4 presents the response of inflation and trade credit growth to positive aggregate productivity (TFP) and monetary policy (Mon. Pol.) shocks in the low- and high-trade credit-to-bank credit economies (solid-blue-asterisk line and dashed-red-diamond line, respectively). Additionally, we plot two models without search frictions, also with high and low trade-to-bank-credit ratio (solid-green-circles and plus lines).

The figure shows that in response to a temporary increase in aggregate productivity, there is no difference in the response of inflation and trade credit growth between the low and the high trade-to-bank credit economies without search frictions, contrary to what we see in the data. However, the variables do show different behavior for the economies with search frictions. the low trade-to-bank credit ratio economy exhibits a small initial fall in trade credit growth before subsequently rising above steady state. In contrast, the high trade-to-bank credit ratio economy shows an increase in trade credit growth that puts more

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Fig. 4. Impulse Response to Positive Aggregate Productivity and Monetary Policy Shocks
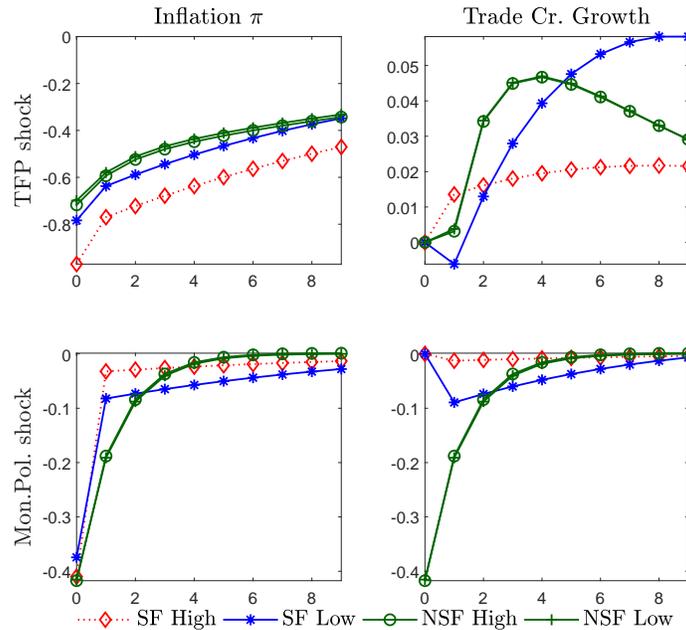
Notes: SF (NSF) corresponds to search (no-search) frictions. High (Low) denotes the economy with a high (low) steady-state trade-to-bank credit ratio. Impulse responses show deviations from steady state.

downward pressure on inflation relative to the low trade-to-bank credit ratio economy. A similar result holds amid a positive monetary policy shock, with the smaller fall in trade credit growth in the high trade-to-bank credit economy putting more downward pressure on inflation. All told, this explains why the negative correlation between inflation and trade credit growth is stronger in high trade-to-bank credit ratio economies.

4.3 Economic Mechanisms

To shed light on the economic mechanisms that can rationalize the new facts in Section 2—both the negative relationship between trade credit growth and inflation in the full firm sample and the role of high trade-to-bank-credit ratio firms in driving this relationship—and the model-based results above, Figures 5 and 6 plot the response to temporary positive aggregate productivity and monetary policy shocks in the two calibrated economies considered above (one with a baseline low steady-state trade-to-bank credit ratio and one with a baseline high trade-to-bank credit ratio).

As we already mentioned above, we focus on a model with search frictions to understand the differences between high- and low- trade-to-bank-credit ratio responses to shocks because a model without search frictions does not capture the facts from the data. There are two main differences between our model with search frictions and a standard model

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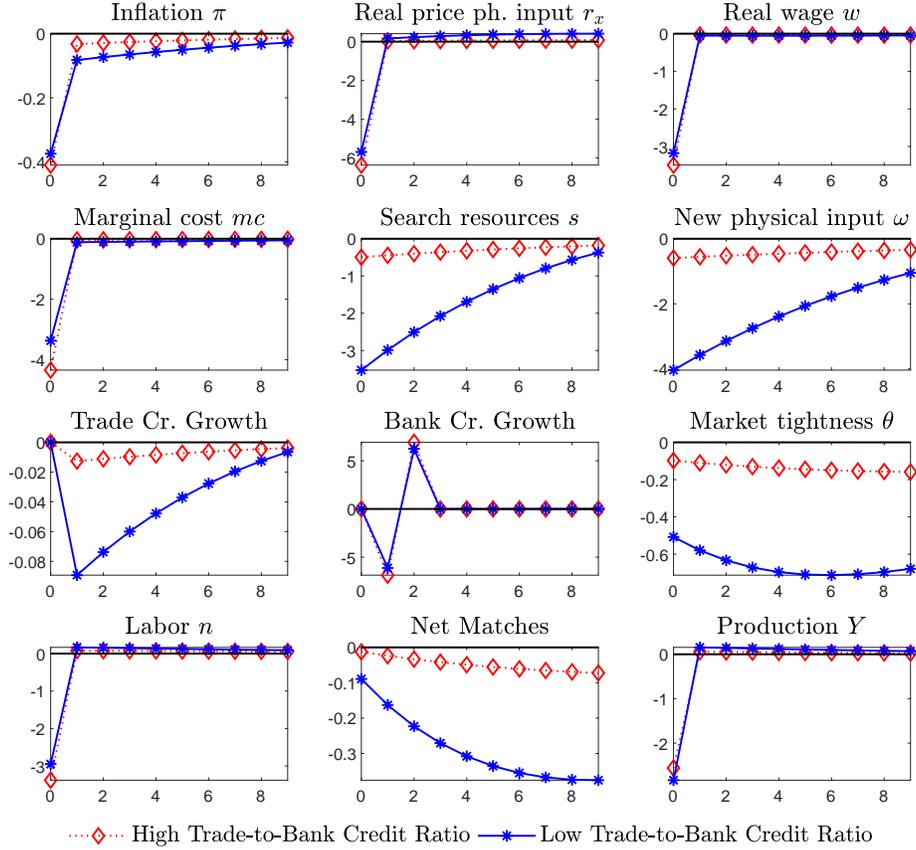Fig. 5. Impulse Response to Positive Aggregate Productivity Shock
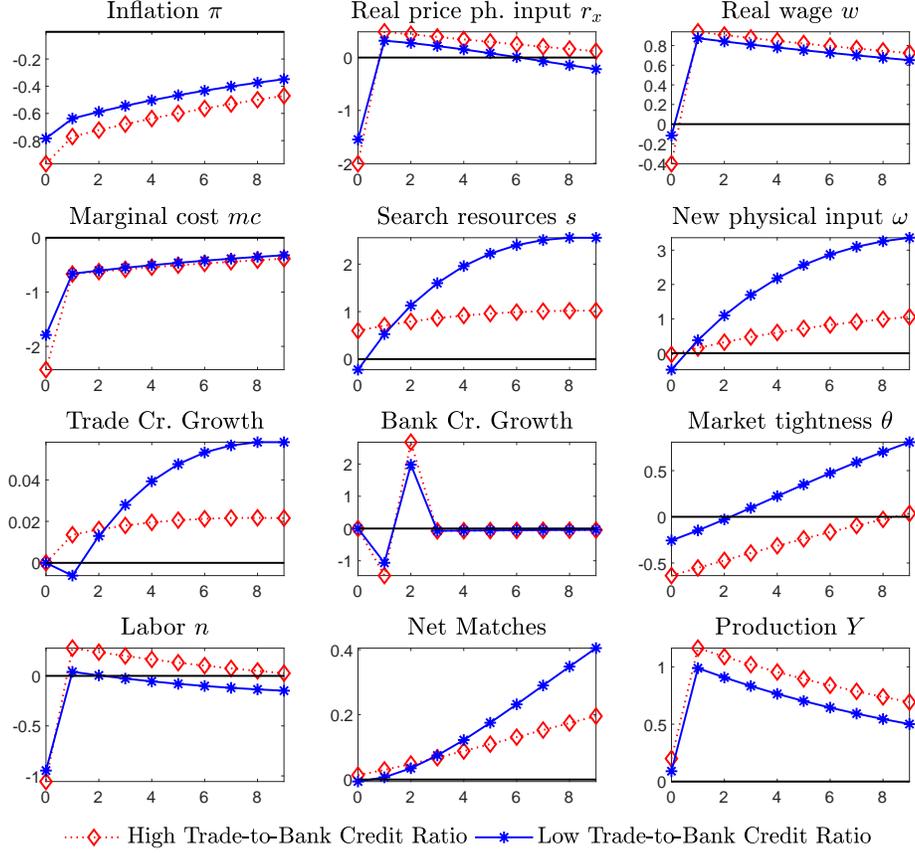
Notes: High (Low) TC Ratio denotes the economy with a high (low) steady-state trade-to-bank credit ratio. Impulse responses show deviations from steady state.

without search frictions. Firstly, net investment takes into account any unmatched capital ω_t as well as the search costs $\kappa(s_t)$, so it tends to be higher than in a Walrasian model. Secondly, the search friction has a measure of market tightness (that is countercyclical) and results key for the mechanism, tending to amplify shocks.

Consider the response to aggregate productivity shocks first. The economy with a high trade-to-bank credit ratio exhibits a sharper reduction in inflation and an initially larger increase in trade credit growth. After the shock, intermediate goods firms take advantage of the shock and can, on impact, decrease labor (which all else equal prompts a decrease in the real wage). However, since physical capital is a stock and predetermined in period t, firms cannot change the physical capital needed for production. Thus, amid a reduction in labor, the marginal productivity of physical capital decreases, which puts downward pressure on the real price of physical inputs. Given that the prices of the two

Fig. 6. Impulse Response to Positive Monetary Policy Shock

Notes: High (Low) TC Ratio denotes the economy with a high (low) steady-state trade-to-bank credit ratio. Impulse responses show deviations from steady state.

goods decreases on impact, the marginal cost of the good decreases and so does inflation. This last movement brings the interest rate down, prompted by the Taylor Rule. Due to the presence of Calvo pricing, the reaction of inflation is persistent. Then, the positive technology shock increases production and brings inflation down persistently. This result is valid for the model both with and without search frictions.

In the presence of search frictions, the marginal value of future matched physical capital increases after the shock. In response to this, more resources are spent to find a match, and s_t increases. In addition, physical input suppliers supply more physical inputs (that is, ω_t is also increasing). This drives an increase in net matches and in net new investment, so there is an increase in demand relative to a model without search frictions. Additionally, because of the increase in s_t and ω_t, market tightness falls and leaves more room for matches in physical input markets. The resulting contraction in market tightness puts downward

pressure on the price of physical input, which then increases after the initial impact. It is worth noting that the drop in inflation is accompanied by an increase in trade credit growth, which is consistent with the stylized facts in Section 2.

In a model without search frictions, changing the trade-to-bank credit ratio at the steady state brings marginal changes to the impulse response functions after a technology shock. In contrast, the model with search frictions presents non-negligible differences. In particular, a high trade-to-bank credit economy spends more resources on physical input markets *vis-à-vis* a low-ratio economy. Then, relative to a high-ratio economy, the low trade-to-bank credit economy responds by decreasing the total amount of resources spent in physical input markets proportionately less after a positive technology shock. This leads to a smaller increase in output and, therefore, a smoother reaction of labor and the price variables, such as the wage, the real price of physical input, the marginal cost and, therefore, inflation. Because of the increase in future marginal productivity of physical inputs as a result of the shock, the resources spent on search and the accumulation of physical inputs increase after the initial shock but in a smoother way in comparison to the high trade-to-bank credit economy. Additionally, and in contrast to a high trade-to-bank credit economy, the low trade-to-bank credit ratio economy experiences a small drop in trade-credit growth right after the initial shock with a decrease in inflation, not presenting a clear path, similar to what we showed in Section 2. The overall reaction of the low trade-to-bank credit ratio economy is still larger than the one from an economy without search frictions.

The general mechanism we just described is present amid a positive monetary policy shock, with the exception that in the case of this last shock, demand for trade credit (reflected in s_t) falls in the two economies. Importantly, though, the fall in demand is smaller in the high trade-to-bank-credit ratio economy since the rise in nominal interest rates has, *initially*, a smaller adverse effect on the the effective wage bill. As a result, intermediate goods firms' perceived matching probability falls by less which, *all else equal*, limits the fall in the price of physical inputs that would occur otherwise. Amid this endogenous rigidity, firms reduce their labor demand by more, leading to a larger fall in the marginal product of physical inputs that, in equilibrium, more than offsets this rigidity and ultimately leads to a larger fall in the Nash price. The behavior of labor demand ultimately leads to a larger reduction in wages on impact (similar to the response in the price of physical inputs), so that the marginal cost falls by more and contributes to a sharper initial reduction in inflation. Similar to the case of productivity shocks, the correlation between trade credit growth and inflation is stronger in economies with a high steady-state trade-to-bank credit ratio.

A clarifying note is in order. As suggested by Figure 4, amid a monetary policy shock, inflation and trade credit growth move in the same direction. This may initially suggest that monetary policy shocks cannot reconcile the empirical evidence in Table 4 since such evidence suggests a *negative* relationship between these two variables. Specifically, the model suggests that both trade credit growth and inflation fall (rise) in response to a

positive (negative) monetary policy shock. Critically, though, the *smaller* is the fall in trade credit growth (which is associated with a high steady-state trade-to-bank credit ratio economy), the *larger* is the fall in inflation. In other words, *in relative terms*, trade credit growth does put downward pressure on inflation, which is consistent with the data (see Table 4). As noted earlier, though, the model's success in qualitatively capturing the negative relationship between trade credit growth and inflation in the data is primarily driven by aggregate productivity (or supply) shocks, with monetary shocks being second order.

4.3.1 The Role of Trade-Credit-Based Inputs in Production

Our model is readily suitable to explore which structural firm features may explain the role of trade credit growth in affecting price dynamics. We find that changing α to obtain alternative steady-state trade-to-bank-credit ratios is critical to be able to generate a stronger negative relationship between trade credit growth and price dynamics in high trade-to-bank-credit firms, as observed in the data. For example, reducing the fraction of the wage bill that is financed with bank credit or lowering the cost of searching for input suppliers in the baseline (low trade-to-bank-credit) economy in order to generate a high trade-to-bank-credit ratio economy fails to replicate the facts in the data, either quantitatively (in the case of search costs), or qualitatively (in the case of the working capital constraint). This experiment with alternative structural parameters suggests that it is the higher intensity of trade-credit-based inputs in the production process—*which, incidentally, is associated with the segment of firms that have a high trade-to-bank-credit ratio*—that is ultimately responsible for explaining the stronger link between trade credit growth and inflation in high trade-to-bank-credit ratio firms within the context of our model. Put differently, factors pertaining to firms' production process (which are unobservable due to the limitations of our firm-level dataset since the latter only provides balance sheet information) and not the trade-to-bank-credit ratio *per se* can explain the fact that high trade-to-bank-credit ratio firms exhibit a stronger relationship between trade credit growth and inflation in the data.

4.3.2 The Role of Search Frictions

Interfirm trade credit is rooted in long-term relationships between input suppliers and customers, which are costly and time-consuming to establish. Thus, search frictions are a natural way to capture trade credit. These frictions play a relevant role beyond simply embodying long-term relationships between intermediate goods firms and physical input suppliers.

To show this explicitly, we shut down search frictions in our benchmark model.[26] Figures 7a and 7b show that, absent search frictions, the model does generate an empirically-

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[26] Appendix D presents the equilibrium conditions of a frictionless version of our benchmark model. Effectively, amid frictionless physical input markets, the model collapses to a standard New Keynesian model with physical input accumulation. We allow for standard quadratic adjustment costs for physical

Fig. 7. Simulated Time Series: Inflation and Trade Credit Growth, Low and High Trade-to-Bank-Credit Ratio, No Search Frictions

(a) Low Trade-to-Bank-Credit Ratio   (b) High Trade-to-Bank-Credit Ratio
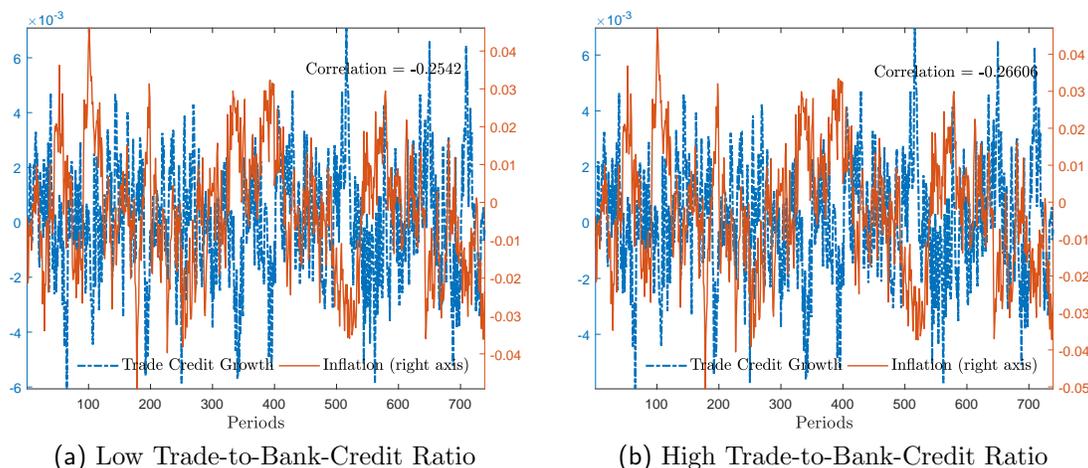
consistent negative relationship between trade credit growth and inflation, but the differences in the correlation between an economy with a low steady-state trade-to-bank credit ratio and an economy with a high ratio are negligible.[27] This traces back to the fact that there is no notion of market tightness in the absence of search frictions. As discussed earlier, market tightness plays an important role in generating differential endogenous changes in the price of physical inputs via intermediate goods firms' matching probability $f(\theta)$ in an economy with a high steady-state trade-to-bank-credit ratio relative to one with a low ratio. Thus, the inclusion of search frictions—which effectively capture the relationship nature of interfirm trade credit, but also imply non-negligible differences in input prices and therefore marginal costs—is important for generating *non-negligible quantitative differences* in the relationship between trade credit growth and price dynamics in an economy with a low steady-state trade-to-bank credit ratio vis-à-vis a high-ratio economy.

4.4 Robustness Checks

We summarize the results of the robustness checks in Table 7.

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inputs since otherwise the model generates excessive volatility in trade credit growth.

[27] We note that absent adjustment costs for physical inputs, the model generates a *positive* relationship between trade credit growth and inflation. This stands in contrast with the facts in Table 4.

Tab. 7. Unconditional Correlation of Inflation with Trade Credit Growth, Bank Credit Growth, Robustness checks, 2009Q3-2016Q4

Correlations	(1) Aggregate	(2) Low T-BC	(3) High T-BC
Data			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-0.0617*	0.0250	-0.1037**
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-0.0073	-0.0480	0.0084
Physical Capital Accumulation			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	0.0324	-0.6399
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	0.0953	0.1194
Alternative Matching Elasticity Parametrization			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	-0.7016	-0.7842
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	-0.0159	-0.0141
Convex Search Costs			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	-0.3168	-0.3522
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	-0.0149	-0.0160
Smaller Working Capital Constraint			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	-0.2866	-0.6607
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	-0.0074	-0.0112
Small Open Economy Model			
$\pi_t, \log\left(\frac{\text{Trade Cr.}_t}{\text{Trade Cr.}_{t-1}}\right)$	-	-0.0909	-0.5412
$\pi_t, \log\left(\frac{\text{Bank Cr.}_t}{\text{Bank Cr.}_{t-1}}\right)$	-	-0.0136	-0.0168

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Notes: Column (1) includes all firms in our sample, column (2) only includes firms with low trade-to-bank credit, and column (3) corresponds to the results for firms with a high trade-to-bank credit ratio.

4.4.1 Different Matching Elasticity, Convex Search Cost, and Working Capital Constraint Parameterizations

Absent empirical evidence on the matching process in input markets, we initially set the matching elasticity parameter $\mu = 0.5$. As a robustness check, we recalibrate the baseline model assuming that $\mu = 2$ and perform the same quantitative experiments. Similarly, our baseline calibration assumed linear search costs $\kappa(s_t) = \psi_s(s_t)^{\eta_s}$ with $\eta_s = 1$. We explore how our findings are affected if we recalibrate the model and set $\eta_s > 1$. We also test the sensitivity of our results to having total search costs in the benchmark model represent a smaller share of output in steady state (0.001 as opposed to 0.01).[28] Finally, we explore whether assuming that intermediate goods firms finance only a portion of their wage bill (and not the full amount) changes our results by setting $\phi_n < 1$. None of these alternative parameterizations change our qualitative results, transmission channels, and main findings.[29]

4.4.2 Model with Physical Capital Accumulation

As noted earlier, Appendix E shows that introducing physical capital via frictionless markets on top of trade-credit-based physical inputs does not change any of our main conclusions. In fact, this simple modification makes our results even more consistent with our empirical facts: the correlation between trade credit growth and inflation is virtually zero in a low steady-state trade-to-bank credit ratio economy, whereas the same correlation is strongly negative in a high steady-state trade-to-bank credit ratio economy (see Figures E.1 and E.3 in the Appendix). Moreover, the economic mechanisms discussed above remain unchanged.

4.4.3 Two-Sector Model

Table 4 in Section 2 shows that the negative (and statistically significant) relationship between trade credit growth and inflation in the full firm sample is driven by firms with a high trade-to-bank credit ratio.[30] Appendix G presents numerical results from a simulation of a two-sector version of our benchmark model that is consistent with the facts in Table 4. The same economic mechanisms described in the one-sector model above continue to

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[28] In Table 4, the coefficient on trade credit growth for the high trade-to-bank-credit ratio firms is roughly four times as large (and statistically significant) as the coefficient for low trade-to-bank-credit firms (which is statistically insignificant). Assuming that search costs absorb 0.001 of total output implies that our quantitative results in terms of the difference in the magnitude of the correlations between trade credit growth and inflation in the high vs. low trade-to-bank-credit ratio economies is very much in line with our empirical findings (with the correlation for the high-ratio firms being four times larger than the one for low-ratio firms).

[29] See Appendix F for more details.

[30] Recall that, while low-ratio firms do exhibit a negative relationship between trade credit growth and inflation, this link is statistically insignificant.

be operative. In particular, as shown in the Appendix, the model is able to generate a negative but *negligible* correlation between firm-specific trade credit growth and firm-specific inflation among *low* trade-to-bank credit ratio firms (as in column (2) of Table 4), and a negative and *non-negligible* correlation between firm-specific trade credit growth and firm-specific inflation among *high* trade-to-bank credit ratio firms (as in column (3) of Table 4). Moreover, in this richer model, *high* trade-to-bank credit ratio firms are the ones that contribute to the model's success in generating a negative and non-negligible relationship between *aggregate* trade credit growth and *aggregate* inflation (as in column (1) of Table 4). The Appendix shows that this last fact can only arise in the model if we allow for a small degree of heterogeneity in the degree of price stickiness alongside the differences in the intensity of trade-credit-based physical inputs in the production process discussed in the benchmark (one-sector) model. Specifically, in order to match the aggregate facts in the two-sector model, high trade-to-bank-credit ratio firms require a smaller degree of price stickiness (coupled with greater intensity in trade-credit-based physical inputs in the production process). Importantly, the fact that these firms need smaller nominal rigidities relative to low-ratio firms in order to match the facts in the data is broadly consistent with Figure B.4. As noted earlier, this figure showed that the standard deviation of inflation among firms with a high trade-to-bank credit ratio is larger, and as such these firms tend to change their prices more than firms with a lower trade-to-bank credit ratio. A reflection of this in our model is the smaller degree of price stickiness among high-ratio firms, which leads to these firms' inflation being more volatile relative to low-ratio firms. All told, our results from a simple one-sector model carry through to a richer two-sector version, where the latter successfully captures the stylized facts in the data.

5   Conclusion

Recent studies have highlighted the role of financial frictions and sectoral heterogeneity in understanding aggregate price dynamics in AEs. Less is known about the determinants of inflation dynamics in EMEs beyond the role of domestic supply shocks, exchange rate movements, oil prices, and external shocks. Recent evidence for these economies suggest that, amid limited access to the banking system and formal credit markets, firms in EMEs display a greater prevalence of trade credit—that is, interfirm financing relationships that take place outside of formal credit markets and the banking system—as a source of external financing relative to their AE counterparts. To the extent that firms' financing structure affects firms' cost structure, the high prevalence of trade credit usage among EME firms may play an important role in firms' price-setting and, importantly, in explaining inflation dynamics in EMEs.

Using a novel dataset that merges goods-level prices underlying the Mexican consumer price index (CPI) with detailed balance sheet information from Mexican publicly-listed firms, we show that trade credit is an important determinant of price dynamics in an extensively-studied and representative EME. Specifically, larger firms (in terms of sales

and employees) tend to use more interfirm trade credit relative to bank credit; these firms use interfirm trade credit as a mechanism to smooth variations in their prices; and third, all else equal, firms with a higher trade-to-bank credit ratio tend to lower prices. A tractable New Keynesian model with search frictions in physical input markets can rationalize these new empirical findings. Our findings stress the importance of interfirm trade credit relationships above and beyond other sources of firms' external finance structure for understanding price dynamics in economies with low levels of domestic financial development where interfirm financing arrangements are particularly prevalent. Our work abstracted from the implications of interfirm trade credit relationships for the effectiveness of monetary policy, as well as the possible consequences for financial stability in an EME context. The framework in this paper provides a transparent environment on which to build in order to explore these and other important issues in EMEs in future work.

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