# Three Essays in Empirical Macroeconomics and Finance

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| Dekan: | Prof. Dr. Jürgen von Hagen |
| Erstreferent: | Prof. Dr. Christian Bayer |
| Zweitreferent: | Prof. Dr. Benjamin Born |

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# Content

# Introduction

This thesis contains three essays belonging to different strands of empirical macroeconomics and finance literature. Chapter 1 and Chapter 2 investigate the transmissions of uncertainty shocks in emerging market economies. Chapter 1 studies the impact of financial frictions on the transmissions of uncertainty shocks. Chapter 2 explores the relationship between aggregate uncertainty and firms' access to trade credit while taking the interactive role of social trust into consideration. Chapter 3 considers the role of social connections in the transmissions of monetary contraction shocks. Chapter 1 and Chapter 3 are based on joint work with Sihao Chen and Axel Wogrolly, respectively.

Chapter 1 studies how financial frictions affect the transmissions of uncertainty shocks in emerging countries. Agents in emerging countries face higher uncertainty in forecasting economic fundamentals. Uncertainty shocks are important in driving business cycle dynamics in these countries. Besides, financial frictions have been proved to be critical to quantify the business cycle dynamics in these economies. How important are financial frictions to characterize the transmissions of uncertainty shocks in emerging countries?

Using a panel of 17 emerging countries, this chapter finds that financial frictions can amplify the impact of uncertainty on real consumption more than the counterparts on real GDP. We explain this finding by stressing the role of durable consumption. With an increase in financial frictions, durable consumption, but not nondurable consumption, declines much more than output in response to uncertainty shocks. This phenomenon is explained through the credit channel. An increase in uncertainty is related to a larger increase in real interest rate in emerging economies with less developed financial systems. Such behaviors will generate more substantial responses of durable consumption to uncertainty shocks than GDP and thus explain the larger response of consumption.

Chapter 2 studies the impact of social trust on the transmissions of uncertainty shocks in emerging countries at the firm level. Social trust can mitigate the impact of market frictions which arise due to the difficulties to enforce contracts, which in turn affects the propagations of macroeconomic shocks. This chapter focuses on how social trust affects the transmissions of uncertainty shocks in emerging countries.

Using firm-level data from 26 emerging countries, this chapter finds that firms in countries with higher levels of social trust obtain more trade credit and suffer small drops in their profitability with an increase in aggregate uncertainty. Besides, those firms in industries which depend on liquid funds more benefit more from the higher social trust. Our results are robust if we exclude the impact of other country-level characteristics and use a new measure of uncertainty shocks.

Chapter 3 studies how social connections affect the transmissions of monetary contraction shocks. In modern society, corporate senior managers build complex social networks via the alumni association or other organizations. These social networks can mitigate the cost of gathering information and enhance trust between parties, which in turn affects the transmissions of monetary contraction shocks.

Using the pair-level sale data from the U.S., we find that the sales between upstream and downstream firms decline in response to monetary contraction shocks. However, if the suppliers and customers are socially connected, the sales reduce less. That is to say, social connections can reduce the negative impact of monetary contraction shocks on pair-level sales. This impact mainly comes from the trade credit channel. When the central bank implements contractionary monetary policies, firms can get less credit from financial institutions like commercial banks, and they want to get more trade credit from their suppliers. As with the suppliers, they prefer providing more trade credit to those connected customers, because they can get more business information via social connections and they think those customers are more trustworthy.

# Chapter 1

# Durable Goods, Financial Frictions and the Transmissions of Uncertainty Shocks in Emerging Market Economies

## 1.1 Introduction

In emerging market economies (EMEs), agents face higher uncertainty in forecasting economic fundamentals and uncertainty shocks are important driving forces for business cycle dynamics (Gourio et al., 2015).[1] Meanwhile, financial frictions are proved to be critical to quantify the business cycle dynamics in these economies (Neumeyer and Perri, 2005; García-Cicco et al., 2010 and Akinci, 2017). A natural question followed by these arguments is that how important financial frictions are to characterize the transmission of uncertainty shocks in EMEs, but this question is rarely discussed.[2] This paper studies the relationship between financial frictions and the impact of uncertainty shocks on real activities, especially on consumption and output in EMEs.

Using a panel of 17 emerging economies, this paper tests the relationship between financial frictions and the transmission of uncertainty shocks. Uncertainty in each country is measured by the logarithm of the realized aggregate stock market volatility in the corresponding country during each quarter. This measure is simple and available in real time, free of revisions and sample selections. Financial development is indexed by the ratio of private credit by banks over GDP. This index is at the yearly frequency, and we transform this annual measure of financial development into quarterly frequencies by letting the quarterly value be identical to the annual value in the corresponding year. The higher that ratio is, the more developed the financial market is, and the lower the level of financial frictions is in EMEs. The impact of uncertainty shocks is unambiguous: an increase in uncertainty is associated with a decline in GDP and other real activities.

To exclude the impact of countries' institutional/cultural features and address the issue that the current real activities such as GDP are heavily determined by their past levels, we use a dynamic panel fixed-effect model. The other important issue that may plague our investigation is that it is difficult to disentangle the effect of financial development on the

[1] This paper uses the logarithm of the stock return volatility to measure uncertainty like Gourio et al. (2015). There are alternative measures of uncertainty shocks. For instance, Carrière-Swallow and Céspedes (2013) address the impact of global uncertainty shocks (shocks from US) in emerging countries. Fernández-Villaverde et al. (2011) use shocks to the volatility of the borrowing premium to explain the volatility of consumption in emerging economies. This shock is also a second-order one that resembles the shock to the stock return volatility.

[2] Using a model with financial frictions and uncertainty shocks, Akinci (2017) discusses the business cycles in EMEs. However, in her work, uncertainty accounts little for the fluctuations in consumption and output. With Chilean and US data, Carrière-Swallow and Céspedes (2013) use an SVAR model to see the differential impacts of financial frictions on the transmissions of uncertainty shock in developed and emerging countries. However, they assume uncertainty shocks for both countries are the same and come from the U.S. This may neglect the impact of uncertainty raised by local factors.

transmissions of uncertainty shocks from the effect of the changes in GDP or other variables on financial development. To address this issue, we lag the index of financial development for one year and study the relationship between the predetermined level of financial development and the subsequent impact of uncertainty on real activities. To further identify the causal influence of uncertainty, we use an instrumental variable strategy that makes use of countries' differential exposures to the global oil price as well as U.S. monetary policy. The identification strategy works well as it passes the first-stage F test and Hansen-J over-identification test.

This paper mainly has two findings. First, at a higher level of financial frictions, an increase in uncertainty is associated with a more substantial decline in GDP as well as consumption. Second, the coefficient on the interaction term of uncertainty and financial development in the regression of consumption is more pronounced than the counterparts in the regression of GDP. Moreover, an increase in financial frictions is associated with a larger decline in the ratio of real consumption to GDP with an increase in uncertainty. This suggests that financial frictions can amplify the impact of uncertainty shocks on real consumption more than the counterparts on real GDP. The second empirical finding seems interesting and different from the corresponding results in developed countries[3]. Business cycles in emerging countries are characterized by the so-called "excess volatility of consumption puzzle" (Aguiar and Gopinath, 2007), which refers to the relatively larger volatility of consumption to that of GDP. Our findings can partly contribute to explaining that puzzle, as uncertainty shocks are important to account for the business cycle dynamics in EMEs.

We propose durable consumption as a potential candidate to explain our empirical findings concerning GDP and consumption. With an increase in financial frictions, durable consumption, but not nondurable consumption, declines much more than output in response to uncertainty shocks.[4] This implies that durable consumption is a potential source to explain the differential magnitudes that financial frictions can amplify the impact of uncertainty on GDP and consumption in emerging countries. Our results are robust to an alternative measure of dependent variables, financial frictions, and uncertainty.

Countercyclical country interest rate is an important characteristic of business cycles in emerging markets, and the interaction of countercyclical risk premium and durable goods

[3]See Carrière-Swallow and Céspedes, 2013; Mumtaz and Thedoridis, 2014.

[4]Financial frictions also amplify the negative effect of uncertainty on nondurable consumption in emerging countries in our empirical analysis. However, the amplifying magnitude between GDP and nondurable consumption is not clear.

is the principal channel to explain emerging market business cycle dynamics (Alvarez-Parra et al. 2013). Financial frictions can strengthen this countercyclical response of real interest rate to uncertainty shocks, which is a potential channel via which financial frictions amplify the impact of uncertainty on durable consumption more than that on GDP. Thus, we can understand the differential amplifying magnitudes of financial frictions on GDP and consumption.

The rest of the paper is organized as follows. Section 2 reviews the literatures related to our paper. Section 3 introduces our dataset, empirical specification and methodology. Section 4 reports our empirical findings and explains these findings. Section 5 concludes.

## 1.2 Literature Review

Our paper is closely related to Carrière-Swallow and Céspedes (2013), henceforth CC. Using an open-economy VAR approach, they find that emerging countries suffer much more severe falls in investment and private consumption in response to exogenous global uncertainty shocks compared to US and other developed countries. Furthermore, the credit channel can account for up to one-half of the increased fall in investment generated by uncertainty shocks among emerging economies with less developed financial systems. While our paper also focuses on the impact of financial frictions on the transmission of uncertainty shocks, it differs substantially in three aspects. First, the real activities we mainly focus on are different. Our paper concentrates on the transmissions of uncertainty shocks to GDP as well as consumption and further explain the differential amplifying magnitudes of financial frictions between them in emerging countries. We link this phenomenon to "excess volatility of consumption puzzle" and propose durable consumption as a potential source to explain it. CC, however, pay close attention to the differential responses of investment between developed and emerging countries. Second, in our analyses, the level of financial frictions is indexed by the ratio of private credits by banks to GDP, which is time-varying, but not influenced by the transmission of uncertainty shocks. However, CC regard the credit spread as the measure of financial frictions and it is affected by uncertainty. Their analyses are more like our analyses about the real interest rate. Finally, we use the standard deviation of local stock return as the index of uncertainty shocks which resemble total uncertainty in Gourio et al. (2015), while the shock in CC is constructed according to VIX index and more like a global uncertainty shock.

The focus on the transmissions of uncertainty shocks in EMEs links our paper to a recent branch of literature that explores empirically and theoretically the transmissions of uncertainty shocks in both developed and emerging countries.[5] Among the literature, some of them specialize in the interaction of financial/credit frictions and uncertainty shocks. Alfaro et al. (2018), using a partial equilibrium model and a novel instrumentation strategy, find that financially-constrained firms will reduce investment and hiring more by cutting more short-term debt and hold more cash when facing higher uncertainty. In an otherwise standard DSGE model with BGG financial accelerator, Christiano et al. (2014) find that shocks to the volatility of cross-sectional idiosyncratic capital efficiency are far more important than the other shocks and can account for 62 percent of the fluctuations in output. They argue that financial frictions (monitoring cost in BGG) introduce a premium to cover the costs of default by the entrepreneurs. This premium is high with high uncertainty, leading a low credit to the entrepreneurs. Entrepreneurs can acquire less raw capital with fewer financial resources and thus investment falls. Output, consumption and employment fall following this decline. Akinci (2017) extends Christiano et al.'s work to EMEs. Different from Christiano et al., uncertainty is modeled as the volatility of intermediate input efficiency in emerging markets. She embeds a type of financial frictions with a micro foundation in the emerging market business cycle models and finds that the interaction of uncertainty and financial frictions is important to characterize the cyclical behavior of real interest rate. Our paper provides some empirical evidence on this mechanism of the interaction, but further considers the interaction of uncertainty and financial frictions on durable and nondurable consumption. Cesa-Bianchi and Fernandez-Corugedo (2018), following the spirit of Christiano et al., compare the transmissions of micro uncertainty shocks as well as macro uncertainty shocks under different levels of financial frictions. They find that credit frictions can apparently amplify micro uncertainty shocks because they act through the cost of external debt and capital demand while macro uncertainty shocks are less affected by credit frictions due to its transmission via precautionary savings. However, in our paper, we empirically point out that financial frictions can also amplify the impact of macro uncertainty.

Our paper is also related to Álvarez-Parra et al. (2013), who firstly argue that the interaction of durable consumption and financial frictions is vitally important to characterize the business cycles in EMEs. During economic expansions, for instance, consumers take advantage of the lower interest rate by borrowing more in order to increase the stock of

[5] To name a few: Bloom et al. (2007); Bloom (2009); Asker et al. (2014); Gilchrist et al. (2014); Barrero et al. (2017); Arellano et al. (2018); Bloom et al. (2018) ; and Bayer et al. (2019) have studied the impact of uncertainty in developed countries, Fernández-Villaverde et al. (2011) and Guorio et al. (2015) in emerging countries, Mendicino and Zhang (2018) use a small open economy framework but calibrate their model to Canada.

durables as well as capital. Since durable goods are tradable, part of the accumulation of durables and capital resorts to imports. As a result, net exports fall more and consumption expenditures and investment increase more during expansions, making consumption more volatile relative to output. Our paper follows their arguments and provides some empirical evidence. However, the driving force in our paper is uncertainty shocks. Apart from EMEs, the durable good channel is also widely used to explain the business cycles in developed countries. Monacelli (2009), for instance, shows that borrowing constraints, where durables play a role of collateral assets, help to explain the transmissions of monetary policy shocks.[6]

Finally, our paper belongs to the literature on business cycles in EMEs, especially on the "excess volatility of consumption puzzle". One strand of literature (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Garcia-Cicco et al., 2010; Akinci 2017) emphasizes the importance of interest rate shocks and financial frictions. Once the country spread goes up, the interest rate cost to finance working capital is higher and firms reduce productions. Consumers will reduce their consumption partly due to income effect. Our paper provides an empirical analysis of the financial friction channel to characterize business cycle dynamics in EMEs but introduces uncertainty shocks as the driving force. We find that the interaction of uncertainty and financial frictions help to explain the excess volatility of consumption.

## 1.3 Data, Specification and Methodology

We describe our sample at first, then the empirical specification and methodology we use.

### 1.3.1 Data

This project focuses on the transmissions of uncertainty shocks in EMEs. Our sample countries include Bulgaria, Chile, Columbia, Czech Republic, Estonia, Hungary, Israel, Korea, Mexico, Poland, Portugal, Romania, South Africa, Slovenia, Slovakia, Thailand, and Turkey.[7] The sample extends from 1970 Q1 to 2013 Q1.[8] However, some series start later than others. The descriptive statistics are presented in Table 1.1. To see whether the impact of financial frictions in EMEs is different from that in developed countries, we repeat some regressions with a sample of developed countries. This sample includes Australia, Austria,

[6]More research see Mertens and Ravn (2011) and Sterk (2010).

[7]We use these 17 countries due to data availability. Data for durable and nondurable consumption is only available in these countries. More emerging countries, such as Argentina and Brazil, can be covered when we only consider the regressions of real GDP, consumption, investment and trade balance. The results are consistent with ours.

[8]As with the Eastern countries, their data starts after 1995Q1.

Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Netherland, New Zealand, Spain, Sweden, UK, and USA. The sample also extends from 1970 Q1 to 2013 Q1. The descriptive statistics are presented in Table 1.2.

Table 1.1
**Descriptive Statistics of Emerging Countries**

| **Dep-Vars** | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|
| GDP (in logs and HP filter)*100, Y | 0 | 2.40 | -7.94 | 7.08 |
| Consumption (in logs and HP filter)*100, C | 0 | 3.17 | -10.05 | 9.86 |
| Durable (in logs and HP filter)*100, D | 0 | 8.67 | -24.63 | 20.98 |
| Nondurable (in logs and HP filter)*100, N | 0 | 2.43 | -7.45 | 8.49 |
| $\frac{C}{Y}$, % | 59.77 | 6.33 | 46.94 | 72.57 |
| **Indep-Vars** | | | | |
| log(Real effective exchange rate) | 4.48 | 0.20 | 3.73 | 4.88 |
| CPI | 56.96 | 32.68 | 0.15 | 116.67 |
| log(Volatility) | -4.69 | 0.34 | -5.30 | -3.62 |
| FD (Private Credit/GDP) | 45.03 | 27.98 | 2.75 | 165.86 |

**Note**: Our sample countries include Bulgaria, Chile, Columbia, Czech Republic, Estonia, Hungary, Israel, Korea, Mexico, Poland, Portugal, Romania, Slovenia, Slovakia, South Africa, Thailand, and Turkey. The definition of emerging economies is according to Morgan Stanley Strategy Indexes (MSCI). $\frac{C}{Y}$ the ratio of real consumption to GDP. To understand the results more directly, the index of uncertainty (log(Volatility)) is normalized to 0 mean and unit standard deviation in all tables other than Table 1.1 and Table 1.2.

Table 1.2
**Descriptive Statistics of Developed Countries**

| **Dep-Vars** | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|
| GDP (in logs and HP filter)*100, Y | 0 | 1.63 | -7.08 | 11.22 |
| Consumption (in logs and HP filter)*100, C | 0 | 1.49 | -8.71 | 13.24 |
| Durable (in logs and HP filter)*100, D | 0 | 4.95 | -21.95 | 32.46 |
| Nondurable (in logs and HP filter)*100 , N | 0 | 1.09 | -6.51 | 6.75 |
| $\frac{C}{Y}$, % | 53.78 | 8.30 | 30.33 | 71.43 |
| **Indep-Vars** | | | | |
| log(Volatility) | -4.58 | 0.40 | -5.53 | -3.30 |
| FD (Private Credit/GDP) | 89.30 | 41.50 | 18.53 | 262.46 |

**Note**: Our sample countries include Australia, Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, New Zealand, Spain, Sweden, UK, and USA.

**Macroeconomic Data.** Real GDP, consumption, investment, export, and import series in national currency are from the International Monetary Fund's (IMF) International Financial Statistics (IFS), Organisation for Economic Co-operation and Development (OECD) statistics, Eurostat, and Global Financial Data (GFD) other than South Africa. The data of South Africa comes from Central Bank of South Africa. As those 5 databases mentioned above are adjusted now and then, some data is missing. Real durable and nondurable consumption other than Chile, Mexico, Thailand, South Africa, and Turkey are obtained from OECD and Eurostat. We obtain Chile, Mexico, Thailand, and South Africa's data for durable and nondurable from their central banks and Turkey's data from Turkish Statistical Institute.[9] Those series are quarterly and seasonally adjusted by using Census x12 method. The seasonally adjusted series are then in logs and detrended by HP filter. The data is winsorized at the 1% level. CPI-based real effective exchange rate (REER) is used to represent the real exchange rate. Quarterly REER data is from IFS and BIS and also seasonally adjusted. The data for capital account openness is obtained from Chinn-Ito Fi-

[9]For durable consumption data of Thailand and Turkey, to get long-term data, we construct durable consumption by calculating the sum of expenditures on furnishing, household equipment, vehicles, etc.

nancial Openness Index. Finally, we construct data for the country-level leverage ratio based on Fernández and Gulan (2015) and obtain the raw data from COMPUSTAT.

**Financial Data.** Stock market return and stock market volatility are based on Baker et al. (2018) who in turn rely on GFD.[10] In the empirical work, the logarithm of stock market volatility serves as the index of uncertainty. The financial development variable is indexed by the ratio of private credit by banks over GDP and is based on Čihák(2013) and the World Bank Open Data. Interest rate comes from Uribe and Yue (2006), Eurostat and Federal Reserve Banks of St Louis. These data is in logarithm.

### 1.3.2 Empirical Specification

This paper intends to study the relationship between financial frictions and the transmissions of uncertainty shocks in EMEs. However, implementing a convincing empirical test raises some important issues. One of these issues is that institutional/cultural features that may be correlated with financial development may also influence the transmission of uncertainty shocks. For example, Beck et al. (2001) find that historically determined legal traditions shape financial development today. These legal traditions differ across countries and may regulate the ability of central bank or government to accommodate adverse shocks. We are able to address this issue by estimating a fixed-effect model with panel data.

The second issue that may plague our investigation is that it seems difficult to disentangle the effect of financial development on the transmission of uncertainty shocks from the effect of the changes in GDP or other variables on financial development. If higher GDP creates higher levels of financial development, one might expect to find a positive correlation between financial frictions and the impact of uncertainty shocks on GDP, even if financial frictions have no effect on the transmission of uncertainty shocks to GDP. We attempt to address this issue by lagging the index of financial development for one year. We study the relationship between the one-year predetermined level of financial development and the subsequent impact of uncertainty on the real economy in EMEs. In our robustness check, we assume that the level of financial development is time-invariant and define the ratio of private credit by banks over GDP in 1998 as the index of financial development for the whole periods. Nonetheless, neither of our proposed solutions solve this endogeneity problem entirely and we remain cautious in our interpretation. In addition, the other important issue that affects our investigation is that the variation in country-level stock return volatility may

[10] As with the countries whose data is not available in Baker et al. (2018), we construct them ourselves.

be endogenous to GDP as well as other real activities. The most likely source of this endogeneity comes from omitted variables because some other country-level shocks may affect the country-level stock return volatility and the real economy at the same time. This issue may bias the transmission of uncertainty shocks to the real economy in emerging countries. To overcome this issue, we exploit countries' differential exposure to U.S. monetary policy and energy price to generate the corresponding country's stock market volatility, and then implement the instrumental variable strategy to identify the transmission of uncertainty shocks.

Finally, the current real activities such as GDP are heavily determined by their past levels. Thus, we include the one-period lagged dependent variables as controls. Based on Keele and Kelly (2005), a model with lagged dependent variables is the best choice if history matters and the process of dependent variable is stationary. After considering the issues discussed above, we assess the relationship between financial frictions and the transmission of uncertainty shocks using the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1}$$

$$+\beta_3 * FD_{i,t-1} + \rho Y_{i,t-1} + \delta' Z_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$$

,

where $Y_{i,t}$ denotes the detrended logarithm of real GDP or other indicators of country $i$ in period $t$. $log(Volatility)_{i,t-1}$ is the one-period lagged logarithm of quarterly standard deviation of stock daily returns and serves as the index of one-period lagged uncertainty. $FD_{i,t-1}$ denotes the predetermined level of financial development[11] and is indexed by the ratio of private credit by banks over GDP lagged for one year. Here, financial frictions are assumed to increase when $FD_{i,t-1}$ decreases. The interaction of lagged uncertainty and financial development, $log(Volatility)_{i,t-1} * FD_{i,t-1}$, captures the differential impacts of uncertainty on GDP or other dependent variables across countries with different levels of financial frictions. Country fixed effects are included to control for omitted country characteristics. Errors are clustered at the country and year level. [12] Time fixed effects are also included so as to capture time trends affecting all countries in the sample.

$Z_{i,t-1}$ are additional control variables that may help to explain the business cycles in EMEs. In emerging countries, the openness to the international market is a key factor in

[11] Although lagged for one year, $FD_{i,t-1}$ may be not exogenous because sometimes people make decisions on investment next year but borrow one year in advance. Then GDP next year may affect the private credit this year

[12] In some regressions, errors are not clustered due to the low number of groups.

predicting the economic dynamics. There is a series of literature (Meza and Urrutia, 2011 and Seoane, 2016) addressing that real exchange rate makes a difference in shaping business cycle dynamics in EMEs. Real exchange rate is thus considered in the empirical specification as a matter of course. Finally, inflation is another potential candidate that reflects the fundamental development of the economy. $Z_{i,t-1} = [CPI_{i,t-1}, RER_{i,t-1}, Openness_{i,t-1}]'$ is the vector of control variables in which CPI and real exchange rate are lagged for one quarter while the index of capital account openness is lagged for one year. Here, $CPI_{i,t-1}$ and $RER_{i,t-1}$ denote the consumer price index and real effective exchange rate for country $i$ in period $t-1$, respectively. $Openness_{i,t-1}$ is the one-year lagged Chinn-Ito Financial Openness Index.

### 1.3.3 Identification

The identification strategy in this paper depends on the fact that different countries are exposed to global monetary policy and energy price in different degrees to generate exogenous changes in country-level uncertainty. The idea is that some countries are very sensitive to US monetary policy (e.g., Korea) because they hold a large amount of U.S. treasury securities while others not. Thus, when U.S. monetary policy uncertainty rises, country-level uncertainty increases more in the former group than the latter one. Meanwhile, different countries have different energy structures, so that changes in oil price volatility generates differential moves in country-level uncertainty.

This approach is similar to Alfaro et al.'s (2018) identification strategy based on Stone and Stein (2013). In Alfaro et al.'s work, they instrument firm-level uncertainty by exploiting firms' differential exposure to energy, currency and policy.

We estimate each country's sensitivities to oil price and U.S. monetary policy as the factor loadings of a regression of one country's quarterly stock return on oil price and U.S real interest rate. That is to say, for country $i$, we estimate sensitivities to oil price and U.S. monetary policy, $\beta_i^p$ and $\beta_i^m$, as follows:

$$r_{i,t} = \alpha_i + \beta_i^m * r_{us,t} + \beta_i^p * P_{oil,t} + \Gamma * X_t + \epsilon_{i,t}$$

where $r_{i,t}$ is country's quarterly stock return, $r_{us,t}$ is quarterly real interest rate, and $P_{oil,t}$ is the quarterly change in oil price. $X_t$ is the vector of control variables related to stock return.

As with oil price, we use the global price of WTI and calculate the quarterly implied volatility of its monthly change, $\sigma_{oil,t}$, as the measure of their uncertainty. As with monetary policy, we construct U.S. real interest rate by dividing effective federal funds rate into CPI and use Husted et al's (2017) index, $MPU_{us,t}$, as U.S. monetary policy uncertainty. The two composites of sensitivity and uncertainty, $\|\beta_i^m\| log(MPU_{us,t})$ and $\|\beta_i^p\| log(\sigma_{oil,t})$, are then the instrumental variables for country-level uncertainty, where the first term in each instrument is the absolute value of the sensitivity[13] we estimate above at the country level. Likewise, the interaction terms with uncertainty included are instrumented by the interaction of the same set of oil price exposure and U.S. monetary policy exposure with the rest variables. For example, the interaction of financial frictions and uncertainty, the main variable we are interested in, is instrumented by the interactions of financial frictions with $\|\beta_i^m\| log(MPU_{us,t})$ and $\|\beta_i^p\| log(\sigma_{oil,t})$.

## 1.4 Result

This section focuses on how financial frictions propagate uncertainty shocks to the real economy in emerging countries. Our empirical analyses are based on two steps. We begin by examining the differential responses of GDP and consumption to uncertainty shocks when emerging economies face differential financial frictions. Next, we decompose consumption into durable and nondurable consumption to understand these differential responses.

In addition to the baseline analyses, we also make several important extensions. First, we check whether our results are robust to an alternative measure of dependent variables, financial frictions and uncertainty. Next, to further identify how financial frictions affect the impact of uncertainty shocks on real activities in emerging countries, we extend our empirical analyses to the real interest rate channel and see how uncertainty shocks are transmitted to real interest rate at different levels of financial frictions. We then control for real interest rate in our baseline regressions and see whether the interaction effects of uncertainty and financial frictions on real activities changes. Finally, our analyses are extended to the interaction of uncertainty and financial frictions on real investment, trade balance and leverage ratio.

### 1.4.1 Baseline Results: GDP and Consumption

We first present some preliminary visual evidence. Figure 1.1 shows the relationship between aggregate uncertainty and GDP and consumption (log and HP filtered) in the low and high financial development groups, respectively. We can see that both GDP and consumption

[13]The sensitivity is equal to 0 if it is not significant at the 5% level in the regression above.

decline more in the lower group as the aggregate uncertainty increases. As with the ratio of consumption to GDP, Figure 1.2 shows that this ratio also decreases more in the lower group.

Table 1.3 shows the impact of financial friction on the propagations of uncertainty shocks to GDP and consumption in EMEs using instrumental variable estimations. The left three columns present the results without additional controls. Column 1 presents the regression of the detrended logarithm of real GDP, column 2 the detrended logarithm of real consumption, and column 3 the ratio of real consumption over GDP. The rest three columns show the results with additional controls. We present the OLS regression results in the Appendix A1.2. Based on the regression results in Table 1.3, we get two important facts concerning the relationship between financial frictions and the transmissions of uncertainty shocks in EMEs.

First, with an increase in financial frictions, an increase in aggregate uncertainty is associated with a larger decline in the detrended logarithm of GDP as well as consumption in EMEs. For example, the positive estimator of the interaction term in column 1, weakly significant at the 10% level, implies that GDP experiences a 0.18-standard-deviation larger contraction if the index of financial frictions move from the 25% quantile to 75% quantile in response a one-standard-deviation positive uncertainty shock. The F-test[14] and Hansen-J p value suggest that the instrumental variables used in the regressions are valid. The amplification effect can be further confirmed by the result presented in column 4 where the coefficient of the interaction term is also positive and weakly significant at 15% level. The result with respect to GDP is in line with recent studies in developed countries (Gilchrist et al., 2014; Cesa-Bianchi and Fernandez-Corugedo, 2018 and Alfaro et al., 2018).[15]

Second, the coefficient on the interaction term in the regression of consumption is more pronounced than the counterparts in the regression of GDP. This finding is robust after we control for capital account openness, real exchange rate and inflation rate. Moreover, when we turn to see the regressions of the ratio of real consumption over GDP, the estimators of the interactions term are positive and significant at the 1% level, while those of the uncertainty terms are negative and weakly significant at the 10% level.[16] These two findings

[14]As there exist two endogenous variables instrumented, the interaction term and the index of uncertainty, a more appropriate first-step test may be Sanderson-Windmeijer multivariate F test developed by Sanderson and Windmeijer (2016). Our regressions can also pass this test.

[15]As with consumption, The situation becomes very tremendous. Our result is inconsistent with some work(Gilchrist et al., 2014 and Mendicino and Zhang, 2018) where the impact of uncertainty on consumption is positive, but consistent with some recent literature (Cesa-Bianchi and Fernandez-Corugedo, 2018; and Bonciani and van Roye, 2016).

[16]To compare the different magnitudes of GDP and consumption, we can also use the difference between

Figure 1.1

**Uncertainty and Aggregate Economy**

GDP

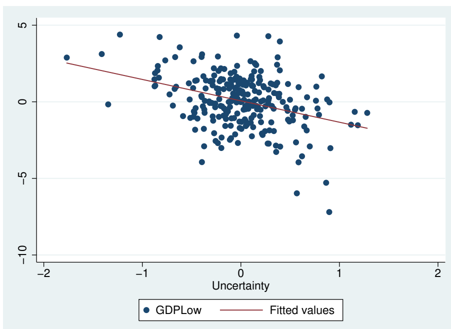



Figure 1.1(a)

GDP

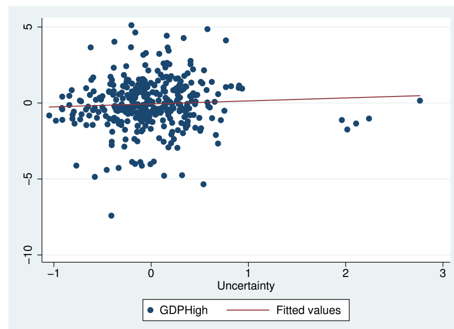



Figure 1.1(b)

Consumption

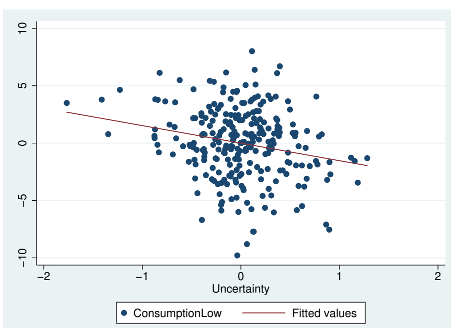



Figure 1.1(c)

Low Financial Development

Consumption

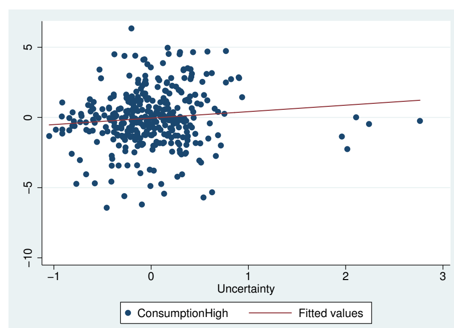



Figure 1.1(d)

High Financial Development

This Figure shows the relationship between aggregate uncertainty and GDP and consumption. Both GDP and consumption are in logarithm and detrended by HP filter. We call the observations whose index of financial development is in the upper quantile the high financial development group (Figure 1.1(b) and 1.1(d)) and the observations whose index of financial development is in the lower quantile the low financial development group (Figure 1.1(a) and 1.1(c)). The X-axis is the index of uncertainty and the Y-axis represents GDP (Figure 1.1(a) and 1.1(b)) and consumption (Figure 1.1(c) and 1.1(d)). We exclude country- and time- fixed effects from uncertainty, GDP and consumption.

Table 1.3
**Benchmark Results**

| Dep-Var | 1<br>GDP | 2<br>Consumption | 3<br>$\frac{C}{Y}$ | 4<br>GDP | 5<br>Consumption | 6<br>$\frac{C}{Y}$ |
|---|---|---|---|---|---|---|
| log(Volatility)*FD | 0.012*<br>(0.0070) | 0.025**<br>(0.012) | 0.016***<br>(0.0056) | 0.012†<br>(0.0082) | 0.025**<br>(0.010) | 0.013***<br>(0.0041) |
| log(Volatility) | -0.16<br>(0.26) | -1.09*<br>(0.65) | -1.27**<br>(0.62) | -0.53<br>(0.38) | -1.13*<br>(0.64) | -1.03*<br>(0.54) |
| FD | 0.11*<br>(0.066) | 0.24**<br>(0.11) | 0.15***<br>(0.054) | 0.11<br>(0.077) | 0.23**<br>(0.099) | 0.13***<br>(0.040) |
| Openness | | | | 0.0038<br>(0.048) | 0.086<br>(0.10) | -0.012<br>(0.097) |
| CPI | | | | 0.014<br>(0.029) | -0.0042<br>(0.035) | 0.012<br>(0.019) |
| RER | | | | 0.0063<br>(0.012) | 0.034*<br>(0.018) | 0.010*<br>(0.0058) |
| 1st Dep-Val | 0.70***<br>(0.063) | 0.63***<br>(0.077) | 0.86***<br>(0.020) | 0.76***<br>(0.028) | 0.65***<br>(0.072) | 0.88***<br>(0.024) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| First-Step F-test 1 | 4.20 | 7.39 | 7.56 | 5.82 | 6.25 | 6.17 |
| First-Step F-test 2 | 2.20 | 3.18 | 3.39 | 2.30 | 2.60 | 2.49 |
| Hansen-J P-Value | 0.29 | 0.21 | 0.64 | 0.36 | 0.53 | 0.50 |
| Observations | 1,286 | 1,213 | 1,213 | 1,146 | 1,134 | 1,134 |
| Group | 17 | 17 | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The table presents the IV estimators for the empirical models: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 * FD_{i,t-1} + \rho Y_{i,t-1} + \delta' Z_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The first three columns present the IV estimation results without additional controls (capital account openness, inflation and real exchange rate) and the rest three do with additional controls. Standard errors are clustered at the country level. The dependent variables are the detrended logarithm of real GDP, consumption and the ratio of real consumption over GDP. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations between GDP and consumption reflects the fact that consumption data for some countries is not available.

Figure 1.2

Uncertainty and the Ratio of Consumption to GDP

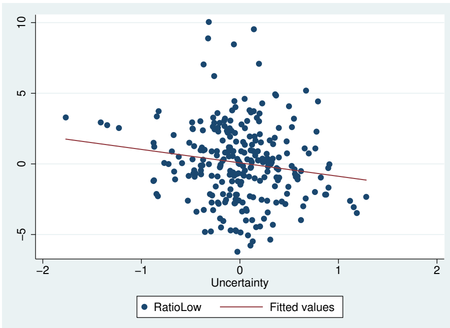



Figure 1.2(a)

Low Financial Development

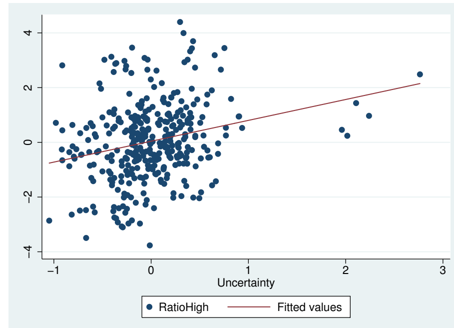



Figure 1.2(b)

High Financial Development

This Figure shows the relationship between aggregate uncertainty and the ratio of consumption to GDP. We call the observations whose index of financial development is in the upper quantile the high financial development group (Figure 1.2(b)) and the observations whose index of financial development is in the lower quantile the low financial development group (Figure 1.2(a)). The X-axis is the index of uncertainty and the Y-axis represents the normalized ratio of consumption to GDP. We exclude country- and time- fixed effects from uncertainty and the ratio.

are quite appealing, as they document a fact that financial frictions amplify the impact of uncertainty on consumption more than the counterparts on GDP in EMEs. To be more concrete, provided that the financial frictions increase by 1 percentage points, consumption experiences a 0.024 percent larger contraction in response a one-standard-deviation positive uncertainty shock, while GDP declines by 0.012 percent more. This fact is different from the existing studies in developed countries such as US, no matter empirical ones (Carrière-Swallow and Céspedes, 2013; Mumtaz and Thedoridis, 2014) or quantitative (Cesa-Bianchi and Fernandez-Corugedo, 2018; Bonciani and van Roye, 2016). It is also different from our own regression results with respect to developed countries. The first three columns in Appendix A1.1 repeat the regressions of the same empirical specification without additional controls using a sample of developed countries. The interaction term loses its significance in the regression of detrended logarithm of consumption. However, we can see that at a high level of financial frictions, greater uncertainty is associated with a larger decline in GDP, but a higher increase in the ratio of consumption over GDP. It can be concluded that higher

the detrended logarithm of consumption and GDP as the dependent variable. The interaction of uncertainty and financial development is also positive and significant, implying that consumption is more volatile than GDP with higher levels of financial frictions.

financial frictions appear to be associated with a lower response of consumption to uncertainty shocks relative to that of GDP in developed countries, which is not only consistent with the existing studies mentioned above, but also opposite to our empirical findings in EMEs.

Let us go back to the regressions with respect to EMEs. The coefficient on the logarithm of stock return volatility is weakly significant at the 10% level in the regression of real consumption. Its absolute value is larger than the counterparts of real GDP in column 1. As with the regression of the ratio between real consumption and GDP, the coefficients on the uncertainty term are also negative and significant at the 5% level. These two findings above imply that the impact of uncertainty on consumption is larger than that on output. We use the estimation in column 5 as an instance. With a one-standard-deviation increase in aggregate uncertainty, real consumption decreases by 1.11 percent, and the ratio of real consumption to GDP decreases by 1.03 percentage points. Business cycle dynamics in EMEs are characterized by the phenomenon called "excess volatility of consumption puzzle" which refers to the fact that private consumption is more volatile than output. Our empirical finding indicates that the uncertainty shocks with poor financial development can partially contribute to explaining this puzzling phenomenon.

### 1.4.2 Baseline Results: Durable and Nondurable Consumption

We propose durable consumption as a potential source to capture the amplification role of financial frictions in propagating uncertainty shocks and generating a larger response of real consumption than the counterparts of real GDP. Durable consumption expenditures, similar to investment, respond much more to shocks, such as TFP and financial shocks, in the presence of higher financial frictions. There are also a series of literature that documents that financial frictions can amplify the impact of uncertainty on investment on a large scale.[17] A natural inference is that financial frictions can significantly amplify the impact of uncertainty shocks on durable consumption like real investment. In an attempt to test the role of durable consumption, we conduct exercises on both durable and nondurable consumption with the same empirical specifications. The question is similar: to what extent financial frictions can amplify the impact of uncertainty on both durable and nondurable consumption?

Figure 1.3 presents some preliminary visual evidence. It shows the relationship between aggregate uncertainty and durable and nondurable consumption (log and HP filtered) in the

[17] See Gilchrist et al.(2014) and Alfaro et al. (2018)

## Figure 1.3

Durable Consumption

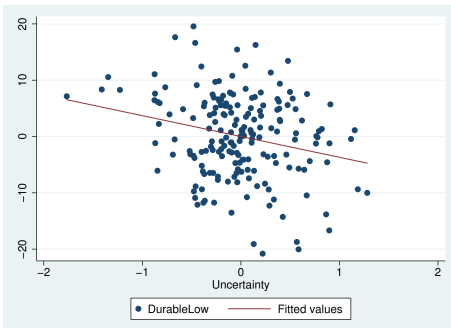



Figure 1.3(a)

Durable Consumption

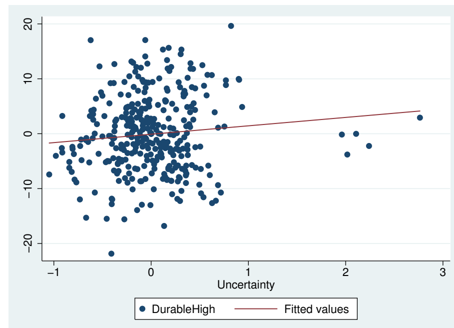



Figure 1.3(b)

Nondurable Consumption

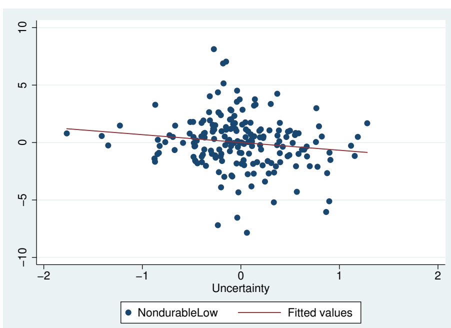



Figure 1.3(c)

Nondurable Consumption

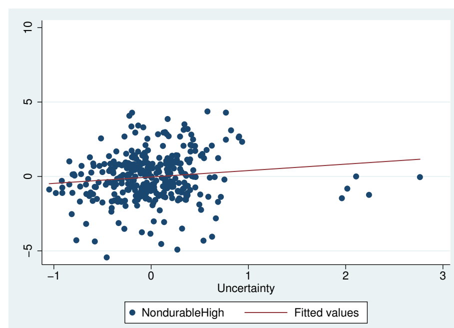



Figure 1.3(d)

**Low Financial Development** **High Financial Development**

This Figure shows the relationship between aggregate uncertainty and durable and non-durable consumption. Both durable and nondurable consumption are in logarithm and detrended by HP filter. We call the observations whose index of financial development is in the upper quantile the high financial development group (Figure 1.3(b) and 1.3(d)) and the observations whose index of financial development is in the lower quantile the low financial development group (Figure 1.3(a) and 1.3(c)). The X-axis is the index of uncertainty and the Y-axis represents durable (Figure 1.3(a) and 1.3(b)) and nondurable consumption (Figure 1.3(c) and 1.3(d)). We exclude country- and time- fixed effects from uncertainty, durable and nondurable consumption.

Table 1.4
**Benchmark Results**

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Dep-Var** | | | | |
| | Durable | Nondurable | Durable | Nondurable |
| log(Volatility)*FD | 0.057* | 0.016* | 0.058** | 0.016† |
| | (0.030) | (0.0098) | (0.028) | (0.010) |
| log(Volatility) | -1.65 | -0.76 | -1.86 | -0.67 |
| | (1.41) | (0.52) | (1.70) | (0.70) |
| FD | 0.53* | 0.15* | 0.54** | 0.15† |
| | (0.28) | (0.092) | (0.27) | (0.098) |
| CPI | | | 0.094 | -0.042 |
| | | | (0.17) | (0.052) |
| RER | | | 0.085** | 0.014 |
| | | | (0.040) | (0.016) |
| 1st Dep-Val | 0.68*** | 0.59*** | 0.68*** | 0.57*** |
| | (0.053) | (0.10) | (0.055) | (0.11) |
| Country FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| First-Step F-test 1 | 5.66 | 5.61 | 5.00 | 4.89 |
| First-Step F-test 2 | 3.06 | 3.15 | 2.03 | 2.10 |
| Hansen-J P-val | 0.16 | 0.21 | 0.27 | 0.43 |
| Observations | 1,062 | 1,062 | 1,025 | 1,025 |
| Group | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. This table presents the results for IV estimations of the detrended logarithm of durable consumption and the detrended logarithm of nondurable consumption. The empirical specification used is that: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 * FD_{i,t-1} + \rho Y_{i,t-1} + \delta' Z_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The first two columns present the estimation results of the empirical specification without additional controls and the rest apply the empirical specification with more controls. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations between them and GDP reflects the fact that durable and nondurable consumption data for some countries is not available.

low and high financial development groups, respectively. We can see that both durable and nondurable consumption decline more in the low financial development group as the aggregate uncertainty increases. In line with the regressions of GDP and consumption, we present the results for empirical specifications with and without controls by applying IV estimation. The results are shown in Table 1.4. The first two columns present the regressions of the detrended logarithm of durable consumption and the detrended logarithm of nondurable consumption without additional control variables, respectively. The rest two present the regressions with additional controls. Also, we use the results of the OLS estimations as robustness checks and we show them in the Appendix A1.3.

First, let us concentrate on the results with respect to durable consumption. We use column 3 as an example and can see that the estimator of the interaction term for IV estimations is significant at the 5% level and larger than the estimators of the corresponding regressions for both consumption and GDP.[18] We find that the impact of uncertainty on durable consumption will increase 0.058 percent with a 1 percentage point increase in financial frictions, over 2 times that on consumption and 5 times that on GDP. At a higher level of financial frictions, durable consumption declines more in response to uncertainty shocks than GDP. Thus, durable consumption can help to explain the reason why real consumption declines more than GDP under the interaction of uncertainty and financial frictions in EMEs. The situations in developed countries are different. In the regressions with a sample of developed countries, Column 4 in Appendix A1.1 shows that the estimators of interaction terms in the regressions of durable consumption is not significant. This implies that financial frictions don't affect impact of uncertainty on durable consumption less than the counterparts on GDP.

What about nondurable consumption? The significant estimators imply that financial frictions also have a negative effect on the impact of uncertainty on nondurable consumption. However, the coefficients on the interaction of uncertainty and financial development are much smaller than the counterparts on durable consumption. Equivalently, financial frictions play an important role in the impact of uncertainty on nondurable consumption as it does in that on GDP, consumption and durable consumption in EMEs, but nondurable consumption

[18]To compare the different magnitudes of GDP and durable consumption, we can use the difference between the detrended logarithm of durable consumption and GDP as the dependent variable. The interaction of uncertainty and financial development is positive and significant, implying that durable consumption is more volatile than GDP with higher levels of financial frictions. As with the difference between nondurables and GDP, the interaction term is not significant. Besides, when we use OLS estimations, the difference between the estimators of durable and GDP is significant at the 10% level.

is not that volatile as durable consumption.

### 1.4.3 Robustness

In this subsection, we conduct a series of empirical analyses to check whether our baseline results are robust to alternative measures of dependent variables, financial development and uncertainty.

#### Alternative Measure of Dependent Variables

In the baseline results, we remove the trend of the logarithms of time series data by HP-filter to make them stationary. This subsection exploits another popular method, first order differencing, to make variables stationary and then explore how financial frictions affect the transmissions of uncertainty shocks in emerging countries.[19] The first difference of the logarithm is equal to the growth rate of the corresponding real activities. The estimation results can reflect to what extent financial frictions amplify the transmission of uncertainty shocks to the growth rate of real activities, such as GDP and consumption in emerging countries.

We expect that an increase in uncertainty is associated with a decline in the growth rate and financial frictions can amplify this negative impact. A positive coefficient on the interaction term is consistent with our predictions. Table 1.5 displays the effects of financial frictions on the propagations of uncertainty shocks where Panel A applies OLS estimations and Panel B IV strategy. IV strategy here works well as it passes the first-step F-test and Hansen J test. We can see that all the coefficients on the interaction terms are positive and (weakly) significant other than the one for durable consumption when IV strategy is applied. Thus, larger uncertainty is associated with a larger decline in the growth rate of real activities in emerging countries when financial systems become less developed. For example, in column 1 in Panel B, If financial frictions increase 1 percentage points, GDP growth rate will experience a 0.028 percentage point larger contraction in response to a one-standard-deviation positive uncertainty shock.[20]

[19] While the objects of using HP filter and first-differencing are both to remove the trend of the logarithms of time series data, the implications for the regressions of the two types of variables are quite different. When using the detrended variables by HP filter as the dependent variables in our regressions, the estimations reflects the interaction of uncertainty and financial frictions on the transitory change of real activities, such as GDP. However, when first differencing is applied, the dependent variables denote the growth rate of the corresponding real activities. The change in the growth rate implies a permanent impact.

[20] Visually, the coefficients of the interaction related to consumption and durable consumption are still larger than the counterpart of GDP in the OLS estimations, as is same with the baseline results. However, we can't say that the interactions on consumption and durable consumption are larger than that on GDP even if we use a dataset in which the available data for all countries are same.

Table 1.5

**Robustness: Alternative Measure of Dependent Variables**

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Panel A: OLS** | GDP | Consumption | Durable | Nondurable |
| log(Volatility)*FD | 0.0085** | 0.012** | 0.029* | 0.012** |
| | (0.0030) | (0.0053) | (0.016) | (0.0046) |
| log(Volatility) | -0.61** | -0.66* | -1.69 | -0.90*** |
| | (0.24) | (0.37) | (1.13) | (0.31) |
| FD | 0.065** | 0.097* | 0.23 | 0.10** |
| | (0.029) | (0.051) | (0.16) | (0.042) |
| 1st Dep-Val | 0.74*** | 0.72*** | 0.74*** | 0.70*** |
| | (0.052) | (0.028) | (0.028) | (0.046) |
| Country Time FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.75 | 0.63 | 0.68 | 0.66 |
| Observations | 1118 | 1118 | 989 | 989 |
| Group | 17 | 17 | 17 | 17 |

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Pannel B: IV** | GDP | Consumption | Durable | Nondurable |
| log(Volatility)*FD | 0.028** | 0.050*** | 0.040 | 0.033* |
| | (0.013) | (0.018) | (0.049) | (0.018) |
| log(Volatility) | -2.02** | -3.35** | -1.64 | -2.05* |
| | (0.94) | (1.71) | (4.22) | (1.11) |
| FD | 0.25** | 0.46*** | 0.33 | 0.30* |
| | (0.12) | (0.17) | (0.48) | (0.17) |
| 1st Dep-Val | 0.72*** | 0.70*** | 0.74*** | 0.67*** |
| | (0.023) | (0.030) | (0.030) | (0.039) |
| Country FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| First-Step F-test 1 | 5.37 | 4.90 | 4.13 | 4.46 |
| First-Step F-test 2 | 2.47 | 2.59 | 1.86 | 2.45 |
| Hansen J P-value | 0.73 | 0.65 | 0.19 | 0.85 |
| $R^2$ | 0.58 | 0.50 | 0.68 | 0.66 |
| Observations | 1118 | 1118 | 989 | 989 |
| Group | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The table presents the IV estimators for the empirical models: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 * FD_{i,t-1} + \rho Y_{i,t-1} + \delta' Z_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. Panel A and Panel B present the OLS and IV regression results respectively. Standard errors are clustered at the country level. The dependent variables are the growth rate of real GDP, consumption durable and nondurable. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty.

Table 1.6

**Robustness: Alternative Measure of Financial Development**

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| **Dep-Var** | | | | | |
| | GDP | Consumption | $\frac{C}{Y}$ | Durable | Nondurable |
| log(Volatility)*FD | 0.0032† | 0.0064** | 0.0019† | 0.022*** | 0.0051** |
| | (0.0021) | (0.0026) | (0.0012) | (0.0059) | (0.0023) |
| log(Volatility) | -0.24* | -0.42** | -0.083 | -1.27** | -0.41** |
| | (0.13) | (0.17) | (0.10) | (0.49) | (0.14) |
| 1st Dep-Val | 0.72*** | 0.62*** | 0.91*** | 0.66*** | 0.55*** |
| | (0.053) | (0.091) | (0.020) | (0.056) | (0.11) |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.75 | 0.55 | 0.97 | 0.60 | 0.46 |
| Observations | 944 | 944 | 944 | 895 | 895 |
| Group | 17 | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. Here FD is the ratio of private credit by banks over GDP in 1998 and the sample period is 2000-2013. This table presents the OLS estimation results and applies the main empirical specification: $Y_{i,t} = \beta_0 + \beta_1 log(Volatility)_{i,t-1} + \beta_2 log(Volatility)_{i,t-1} * FD_{i,1998} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. Errors are clustered at the country level. log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns over the last four quarters and serves as the index of uncertainty. The different number of observations between GDP, durable and nondurable consumption reflects the fact that durable and nondurable consumption data for some countries is not available.

### Alternative Measure of Financial Frictions

This paper focuses on how financial frictions affect the impact of uncertainty shocks on real activities in emerging countries. An appropriate measure of financial frictions is crucial to our regression results. In this subsection, we want to verify that the estimation result does not only hold by the measurement of financial frictions used in the baseline analyses. Here, we propose the level of financial development for each country in 1998 as the financial development indicator for all periods after 1998 and see the effect of initial financial frictions on the impact of uncertainty on each real activities across countries by using the sample after 1998.[21] The empirical specification without additional controls becomes

$$Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,1998} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$$

We repeat all the OLS regressions of the corresponding dependent variables in the baseline estimations and the results are present in Table 1.6.

The estimation results are consistent with the baseline results with the new measure of financial development. First, the coefficients on the interaction terms for GDP, consumption, durable, and nondurable consumption are all positive and (weakly) significant, implying the financial frictions can amplify the effects of uncertainty on real activities in emerging countries. We use the regression of GDP as an example. If financial frictions increase 1 percentage points, the negative impact of uncertainty shocks on GDP will increase 0.0032 percent. Second, the interaction on the ratio of consumption over GDP is still positive and keep its significance at the 15% level, which implies that financial frictions amplify the transmission of uncertainty shocks to consumption more than that to GDP. Furthermore, after decomposing consumption into durable and nondurable consumption, we find that durable consumption will decline more than GDP in response to uncertainty shocks in a less developed financial system, while the magnitude between the effects on GDP and nondurable is smaller. Thus, we conclude that durable consumption is a potential candidate to explain the puzzling empirical finding that real consumption declines more under the interaction of uncertainty and financial frictions.

### Alternative Measure of Uncertainty

To make sure that our results are robust to different measures of uncertainty, we perform our last robustness check by replacing our primary measure with an alternative indicator: the

[21] We use the financial development indicator in 1998 because we can find all the countries' financial development in 1998.

Table 1.7

**Robustness: Alternative Measure of Uncertainty**

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| **Dep-Var** | | | | | |
| | GDP | Consumption | $\frac{C}{Y}$ | Durable | Nondurable |
| log(Volatility)*FD | 0.0091*** | 0.018*** | 0.0049* | 0.048*** | 0.0089* |
| | (0.0025) | (0.0033) | (0.0021) | (0.010) | (0.0045) |
| log(Volatility) | -0.64** | -1.68*** | -0.59* | -3.85*** | -0.88* |
| | (0.20) | (0.27) | (0.26) | (0.73) | (0.41) |
| FD | 0.037** | 0.074*** | 0.026* | 0.20** | 0.036 |
| | (0.011) | (0.017) | (0.011) | (0.057) | (0.021) |
| 1st Dep-Val | 0.63*** | 0.50*** | 0.70*** | 0.70*** | 0.70*** |
| | (0.11) | (0.19) | (0.11) | (0.017) | (0.049) |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.72 | 0.49 | 0.80 | 0.68 | 0.68 |
| Observations | 361 | 361 | 361 | 349 | 349 |
| Group | 8 | 8 | 8 | 8 | 8 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. Here log(Volatility) is the quarterly volatility of daily percentage changes in bond yields and serves as the index of uncertainty. This table presents the OLS estimation results and applies the main empirical specification: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 FD_{i,t-1} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The reduced observations and groups indicate that the index of uncertainty is not available for some countries.

quarterly volatility of daily percentage changes in bond yields. The data for this indicator is obtained from Baker et al. (2018) which in turn reply on GFD.

Also, we repeat all OLS estimations with this measure of uncertainty and Table 1.7 displays the regression results. They again evidently support our aforementioned arguments. First, the estimators on the interaction terms for GDP, consumption and durable consumption keep their significance under 1% confidence interval and are positive. These results confirm the prediction that financial frictions amplify the transmissions of uncertainty shocks to real activities in emerging countries. For example, a one-percentage-point increase in financial frictions is associated with a 0.0091 percent decline in GDP in response to uncertainty shocks (proxied by a one-standard-deviation increase in the quarterly volatility of daily percentage changes in bond yields). Second, we can see that the coefficients on the interaction terms with respect to the ratio of consumption over GDP are positive and significant, which further confirms the empirical finding that an increase in financial frictions is related to a larger decline in consumption relative to GDP in response to uncertainty shocks. What's more, durable consumption is proposed as a potential candidate to understand this empirical finding. With a one-percentage-point increase in financial frictions, durable consumption reduces by 0.048 percent in response to uncertainty shocks while the impact on nondurable consumption is not significant.

### 1.4.4 Real Interest Rate Channel

Fernández and Gulan (2015) document that the countercyclical country interest rate is an important characteristic of business cycles in emerging markets. Alvarez-Parra et al. (2013) emphasize the interaction of countercyclical risk premium and durable goods as the key channel to explaining emerging market business cycle dynamics. The intuition is straightforward: during economic expansion period, real interest rate is low and household borrows to finance their investment as well as the durable goods expenditure. Such behaviors will generate a large volatility of capital and durable good stock and eventually explain the excess volatility of consumption. Moreover, it's expected that financial development matters when lenders decide the charged premium. In this subsection, we verify the hypothesis that financial frictions strengthen the countercyclical response of interest rate to uncertainty shocks.

Table 1.8A shows the results. We can see the estimators of the interaction term and uncertainty are jointly significant. The positive estimators of uncertainty imply that interest rate will increase when uncertainty increases in EMEs. Furthermore, financial frictions can

Table 1.8A

**Interest Rate Channel I**

| **Dep-Var: Interest Rate** | 1 | 2 |
|---|---|---|
| log(Volatility)*FD | -0.0096** | -0.0089** |
| | (0.0040) | (0.0038) |
| log(Volatility) | 1.29*** | 1.21*** |
| | (0.37) | (0.36) |
| FD | -0.033 | -0.022 |
| | (0.048) | (0.046) |
| Openness | | -0.38** |
| | | (0.16) |
| CPI | | -0.053 |
| | | (0.042) |
| RER | | -0.017 |
| | | (0.013) |
| Country FE | Yes | Yes |
| Time FE | Yes | Yes |
| Observations | 816 | 814 |
| $Adj - R^2$ | 0.86 | 0.86 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The table presents the OLS estimators for the empirical models:

$$Y_{i,t} = \beta_0 + \beta_1 log(Volatility)_{i,t-1} + \beta_2 log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 FD_{i,t-1} + \delta' Z_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$$

Standard errors are clustered at the country level. The dependent variables are real interest rate. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations between GDP and real interest rate reflects the fact that interest rate data for some countries is not available.

Table 1.8B

**Interest Channel II**

| **Panel A: Dep-Var** | 1<br>GDP | 2<br>Consumption | 3<br>Durable | 4<br>Nondurable |
|---|---|---|---|---|
| Interest | -0.12* | -0.21* | -0.40* | -0.10† |
| | (0.066) | (0.11) | (0.19) | (0.066) |
| log(Volatility)*FD | 0.0023* | 0.0030* | 0.0076 | 0.0023† |
| | (0.0012) | (0.0017) | (0.0060) | (0.0015) |
| log(Volatility) | -0.11 | -0.25 | -0.70 | -0.24 |
| | (0.091) | (0.21) | (0.62) | (0.20) |
| FD | 0.021 | 0.031 | 0.045 | 0.018 |
| | (0.016) | (0.020) | (0.068) | (0.021) |
| 1st Dep-Val | 0.71*** | 0.61*** | 0.63*** | 0.53**** |
| | (0.040) | (0.087) | (0.066) | (0.12) |
| Country & Time FE | Yes | Yes | Yes | Yes |
| $Adj-R^2$ | 0.78 | 0.56 | 0.59 | 0.60 |
| Observations | 816 | 806 | 737 | 737 |
| **Panel B: Dep-Var** | 1<br>GDP | 2<br>Consumption | 3<br>Durable | 4<br>Nondurable |
| log(Volatility)*FD | 0.0034* | 0.0049** | 0.011† | 0.0032* |
| | (0.0016) | (0.0018) | (0.0064) | (0.0016) |
| log(Volatility) | -0.27** | -0.50** | -1.23** | -0.38** |
| | (0.12) | (0.19) | (0.57) | (0.16) |
| FD | 0.025 | 0.037 | 0.054 | 0.020 |
| | (0.016) | (0.020) | (0.063) | (0.020) |
| 1st Dep-Val | 0.72*** | 0.62** | 0.64*** | 0.53*** |
| | (0.040) | (0.085) | (0.064) | (0.12) |
| Country & Time FE | Yes | Yes | Yes | Yes |
| $Adj-R^2$ | 0.78 | 0.55 | 0.59 | 0.49 |
| Observations | 816 | 806 | 737 | 737 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. Panel A presents the OLS estimation results of the empirical model: $Y_{i,t} = \beta_0 + Interest_{i,t} + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-4} + \beta_3 FD_{i,t-4} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. Panel B present the OLS estimation results of the empirical specification: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-4} + \beta_3 * FD_{i,t-4} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. In this table, we construct a dataset where all data are available. The main difference in observations comes from the fact that some data for interest is missing.

amplify this impact as the estimators of interaction terms are negative. The results are consistent with what we expect above. Financial frictions can strengthen the countercyclicality of interest rate in response to uncertainty shocks. It can be concluded that interest rate is a potential channel to explain the phenomenon that financial frictions amplify the impact of uncertainty on durable consumption more than the counterparts on GDP. As for developed countries, the insignificant estimator in column 6 of Appendix A1.1 implies that financial frictions have little effect on the impact of uncertainty shocks upon real interest rate.

Further, we include interest rate in our regressions, which allows us to parse out the interaction of uncertainty and financial frictions conditional on this important channel. Specially, we consider the following empirical specification:

$$Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-4}$$

$$+\beta_3 FD_{i,t-4} + \alpha Interest_{i,t} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$$

. $Interest_{i,t}$ denotes the real interest rate of country $i$ in period $t$.

Table 1.8B shows the regression results. We can see, once interest rate is added in the regressions, the estimators for the interaction term decrease or become insignificant, which implies that interest rate is an important channel via which financial frictions affect the transmission of uncertainty shocks in EMEs. The coefficients of real interest rate are (weakly) significant and negative, implying that real interest rate has a negative impact on GDP as well as other variables. For example, a one-percent increase in real interest rate implies an almost 0.12 percentage change in GDP. Thus, if we exclude the impact of real interest rate, financial frictions will affect the transmissions of uncertainty shocks in emerging countries less. From the regression on real interest rate, we know that financial frictions can strengthen the countercyclical response of real interest rate to uncertainty shocks. The confluence of results reported in this table is thus consistent with the notion that changes in interest rate are an important part of the mechanism through which financial frictions amplify the impact of uncertainty.

### 1.4.5 Other Variables

In the arguments above, one important reason why we consider the durable consumption as a candidate to explain our empirical findings is that durable consumption is as volatile as investment. Thus, to support our arguments, it is necessary to check to what extent financial frictions amplify the impact of uncertainty on investment. A series of literatures finds that uncertainty has a considerable negative impact on investment via financial friction channel (e.g. Gilchrist et al. 2014; Carrière-Swallow and Céspedes 2013). In this subsection, we check whether this argument holds using our own sample. What's more, for consumption and investment decline more than GDP under the interaction of uncertainty and financial frictions in EMEs, a direct inference is that greater uncertainty is associated with an increase in trade balance and financial frictions amplify the transmission of uncertainty shocks to trade balance. Exercises will be conducted to test this inference in this subsection. Finally, we construct a measure of leverage to explore how financial frictions propagate uncertainty shocks to leverage ratio, for Fernández and Gulan (2015) show that the countercyclical leverage in EMEs is crucial to explain the interest rate channel.

The results are present in Table 1.9 where the first, middle, and last two columns show the regressions of investment, trade balance, and leverage ratio, respectively. The regressions of investment and trade balance apply IV estimations while the counterparts of leverage use OLS estimations[22]. The first stage F-test and Hansen J p value suggest that the IV strategy works well for the regressions of investment and trade balance. The results in this table evidently support our conjectures. First, financial frictions can amplify the impact of uncertainty on investment on a large scale[23]. In column 2, we can see that a 1 percentage point increase in financial frictions leads to a 0.067-percentage-point decline in the impact of uncertainty on real investment. Second, the coefficients on the interaction term is negative and jointly significant with the positive coefficient on the interaction term, which implies that uncertainty has a positive impact on trade balance and financial frictions can propagate this positive effect in emerging economies. Finally, we find that leverage ratio becomes higher in response to uncertainty shocks in emerging countries with a less developed financial system, for the coefficients on the interaction term are negative and significant in the last two regressions.

[22] When apply IV, we find that the estimations of leverage ratio can't pass the first-stage F-test as well as Sanderson-Windmeijer multivariate F test. Thus, we think that OLS estimations are more appropriate. In addition, the 1-period lagged leverage ratio is not included in the regression results we present. However, the regression results don't change much other than that the coefficients on the interaction become smaller and weakly significant under 10% confidence interval.

[23] Here we don't show the results with respect to the ratio of real investment to GDP. However, the coefficients on the interaction in that regression are still positive and significant under 1% confidence interval, implying that financial frictions amplify the impact of uncertainty on real investment more than the counterparts of GDP, like the case in real consumption and durable consumption.

Table 1.9
**Other Variables**

| Dep-Var | 1<br>Investment | 2<br>Investment | 3<br>Trade Balance | 4<br>Trade Balance | 5<br>Leverage | 6<br>Leverage |
|---|---|---|---|---|---|---|
| log(Volatility)*FD | 0.062** | 0.067*** | -0.059*** | -0.065*** | -0.0025** | -0.0025* |
| | (0.024) | (0.020) | (0.022) | (0.020) | (0.0011) | (0.0012) |
| log(Volatility) | -1.59 | -2.63** | 2.05 | 2.83* | 0.11† | 0.12 |
| | (1.41) | (1.25) | (1.53) | (1.62) | (0.070) | (0.079) |
| FD | 0.58** | 0.62*** | -0.056*** | -0.62*** | -0.035* | -0.035* |
| | (0.23) | (0.021) | (0.21) | (0.20) | (0.018) | (0.019) |
| Openness | | -0.016 | | -0.098 | | 0.0036 |
| | | (0.23) | | (0.23) | | (0.041) |
| CPI | | 0.23*** | | -0.019** | | -0.0023 |
| | | (0.081) | | (0.078) | | (0.0096) |
| RER | | 0.044 | | -0.11** | | 0.0010 |
| | | (0.039) | | (0.047) | | (0.0025) |
| 1st Dep-Val | 0.77*** | 0.78*** | 0.65*** | 0.71*** | | |
| | (0.036) | (0.034) | (0.026) | (0.016) | | |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| First-Step F-test 1 | 7.19 | 5.20 | 6.98 | 5.13 | | |
| First-Step F-test 2 | 3.29 | 2.12 | 3.27 | 2.11 | | |
| Hansen J P-Val | 0.90 | 0.93 | 0.69 | 0.68 | | |
| Observations | 1171 | 1092 | 1171 | 1092 | 882 | 869 |
| Group | 17 | 17 | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The table presents the IV estimators for the empirical models: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 FD_{i,t-1} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$ Regressions of investment and trade balance apply IV estimations while those of leverage use OLS estimation. Standard errors are clustered at the country level. FD denotes one-year lagged ratio of private credit by banks over GDP and log(volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations reflects the fact that data for some countries or periods is not available.

## 1.5 Conclusion

This paper documents that financial frictions play an important role in the transmission of uncertainty shocks in emerging countries. We measure economic uncertainty and financial development by the standard deviation of stock market returns and the ratio of private credit by banks over GDP, respectively. Financial frictions can amplify the impact of uncertainty on real consumption more than the counterparts on GDP in these countries. This empirical finding is different from the situation in developed countries where financial frictions affect the impact of uncertainty shocks on GDP more. Decomposing consumption into durable and nondurable consumption, we find that financial frictions can amplify the negative impact of uncertainty on durable consumption more than that on GDP but the impact on nondurable consumption is not clear, which implies that durable consumption is a potential source to explain our empirical finding. The countercyclical real interest rate is an important characteristic of business cycles in emerging markets and we find that financial frictions can strengthen the countercyclicality of real interest rate. During economy contraction periods with a high level of uncertainty, interest rate is high and households save and reduce their investment as well as the durable good expenditure. Such behaviors will generate a larger decline in durable consumption relative to that in GDP in response to a positive uncertainty shock and thus a relatively larger decline in consumption to that in GDP. These empirical findings contribute to explaining the "excess volatility of consumption puzzle" as uncertainty shocks are proved to be an important factor to account for the business cycles in emerging economies.

## 1.6 Appendix

### Developed Countries

In this section we discuss the relationship between financial frictions and the transmissions of uncertainty shocks in developed countries. As is same with the regression in emerging countries, we measure uncertainty in each country using the realized aggregate stock market volatility in that country during each quarter and financial development using the private credit by banks over GDP. We still use detrended logarithm of real GDP, consumption, durable and nondurable consumption by HP filter. Our sample includes 17 developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Netherland, New Zealand, Spain, Sweden, UK and USA. The empirical specification without additional controls and OLS method are applied.

Appendix A1.1 present the regression result with respect to developed countries. The regressions of the detrended logarithm of GDP and consumption, the ratio of consumption over GDP, the detrended logarithm of durable and nondurable consumption, and real interest rate are displayed in turn from Column 1 to Column 6. We can see the interaction doesn't have a significant effect on GDP or consumption. This implies that countries with less developed financial systems have a lower ratio of consumption to GDP in developed countries, which is different from the situations in emerging countries.

After decomposing consumption into durable and nondurable consumption, we find that the interaction term on durable is still not significant, implying that financial frictions have little effect on the impact of uncertainty shock upon durable consumption. From the empirical result above, we deduce that financial frictions mainly affect the transmissions of uncertainty shocks via investment if we simply divide GDP into consumption and investment in developed countries. Real interest rate in developed countries is acyclical as usual. We find that financial frictions has little association with the impact of uncertainty shocks on interest rate.

In conclusion, the effect of financial frictions on the transmissions of uncertainty shock in developed countries is quite different from that in emerging countries. Financial frictions mainly affect the impact on investment and thus GDP in developed countries, while in emerging countries, financial frictions can strengthen the countercyclical response of real interest rate and thus make households save more and consume less durable goods. This help to explain the empirical finding that greater uncertainty is related to a larger decline in consumption relative to that in GDP at a high level of financial frictions in EMEs and contribute to interpreting the "excess volatility of consumption puzzle" in EMEs.

Appendix A1.1
**Developed Countries**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **Dep-Vars** | GDP | Consumption | $\frac{C}{Y}$ | Durable | Nondurable | Interest |
| log(Volatility)*FD | -0.00070 | -0.0031 | -0.0015 | -0.0071 | -0.0032* | -0.016 |
| | (0.0020) | (0.0018) | (0.00098) | (0.011) | (0.0016) | (0.011) |
| log(Volatility) | -0.084 | 0.0039 | 0.035 | -0.15 | 0.017 | 0.48 |
| | (0.049) | (0.065) | (0.040) | (0.37) | (0.051) | (0.55) |
| FD | -0.0046 | -0.016* | -0.0063 | -0.039 | -0.016** | -0.070 |
| | (0.0091) | (0.0082) | (0.045) | (0.15) | (0.0073) | (0.052) |
| 1st Dep-Val | 0.76*** | 0.77*** | 0.95*** | 0.72*** | 0.76*** | |
| | (0.040) | (0.032) | (0.016) | (0.038) | (0.041) | |
| Country & Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,329 | 1,329 | 1,329 | 1,329 | 1,329 | 1,329 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The empirical specification is that $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 * FD_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The table presents the results of the regressions by applying OLS estimations with a sample of developed countries. This sample includes 17 developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Netherland, New Zealand, Spain, Sweden, UK and USA. From column 3, we can get that the ratio of consumption over GDP increase in response to uncertainty shock and the increase in this ratio is higher with a less developed financial system. This implies that financial frictions can amplify the impact of uncertainty on consumption less than that on GDP.

Appendix A1.2

**Benchmark Results-OLS**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **Dep-Var** | GDP | Consumption | $\frac{C}{Y}$ | GDP | Consumption | $\frac{C}{Y}$ |
| log(Volatility)*FD | 0.0036* | 0.0049** | 0.0024** | 0.0031** | 0.0047** | 0.013*** |
| | (0.0018) | (0.0020) | (0.0011) | (0.0014) | (0.0022) | (0.0041) |
| log(Volatility) | -0.29* | -0.42** | -0.22** | -0.25** | -0.41** | -1.03* |
| | (0.14) | (0.16) | (0.076) | (0.11) | (0.17) | (0.54) |
| FD | 0.033* | 0.046** | 0.024** | 0.027 | 0.041** | 0.13*** |
| | (0.018) | (0.020) | (0.011) | (0.015) | (0.022) | (0.040) |
| Openness | | | | 0.011 | 0.11 | -0.012 |
| | | | | (0.030) | (0.95) | (0.097) |
| CPI | | | | 0.0014 | -0.033 | 0.012 |
| | | | | (0.028) | (0.032) | (0.019) |
| RER | | | | 0.0049 | 0.031 | 0.010* |
| | | | | (0.013) | (0.018) | (0.0058) |
| 1st Dep-Val | 0.70*** | 0.62*** | 0.89*** | 0.75*** | 0.64*** | 0.88*** |
| | (0.070) | (0.082) | (0.031) | (0.032) | (0.078) | (0.024) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1286 | 1213 | 1213 | 1146 | 1134 | 1134 |
| Group | 17 | 17 | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; † $p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. The table presents the OLS estimators for the empirical models: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 FD_{i,t-1} + \delta' Z_{i,t-1} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The first three columns present the OLS estimation results without additional controls (capital account openness, inflation and real exchange rate) and the rest three do with additional controls. Standard errors are clustered at the country level. The dependent variables are the detrended logarithm of real GDP, consumption and the ratio of real consumption over GDP. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations between GDP and consumption reflects the fact that consumption data for some countries is not available.

Appendix A1.3

**Benchmark Results-OLS**

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Dep-Var** | | | | |
| | Durable | Nondurable | Durable | Nondurable |
| log(Volatility)*FD | 0.015** | 0.0041** | 0.017** | 0.0035** |
| | (0.0060) | (0.0016) | (0.0068) | (0.0016) |
| log(Volatility) | -0.98* | -0.37** | -1.16** | -0.33** |
| | (0.47) | (0.15) | (0.49) | (0.15) |
| FD | 0.13** | 0.038** | 0.14** | 0.031* |
| | (0.053) | (0.016) | (0.062) | (0.016) |
| CPI | | | 0.044 | -0.062 |
| | | | (0.18) | (0.048) |
| RER | | | 0.082 | 0.013 |
| | | | (0.042) | (0.016) |
| 1st Dep-Val | 0.68*** | 0.55*** | 0.68*** | 0.56*** |
| | (0.056) | (0.10) | (0.058) | (0.12) |
| Country FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 1,062 | 1,062 | 1,025 | 1,025 |
| Group | 17 | 17 | 17 | 17 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; $\dagger\ p < 0.15$. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses. This table presents the results for OLS estimations of the detrended logarithm of durable consumption and the detrended logarithm of nondurable consumption. The empirical specification used is that: $Y_{i,t} = \beta_0 + \beta_1 * log(Volatility)_{i,t-1} + \beta_2 * log(Volatility)_{i,t-1} * FD_{i,t-1} + \beta_3 FD_{i,t-1} + \delta' Z_{i,t-1} + \rho Y_{i,t-1} + I_t + I_i + \varepsilon_{i,t}$. The first two columns present the estimation results of the empirical specification without additional controls and the rest two apply the empirical specification with more controls. FD denotes one-year lagged ratio of private credit by banks over GDP and log(Volatility) is the logarithm of one-quarter lagged the average of quarterly standard deviation of stock daily returns and serves as the index of uncertainty. Openness, CPI and RER denote Chinn-Ito financial openness, consumer price index and real effective exchange rate respectively. The different number of observations between them and GDP reflects the fact that durable and nondurable consumption data for some countries is not available.

# Chapter 2

# Social Trust and Corporate Responses to Aggregate Uncertainty in Emerging Countries

## 2.1 Introduction

Social trust is a broadly defined concept, and it mainly reflects the extent to which others are believed to be honest, upright and reliable. It is a "faith in people". Since Putnam's (1993) contributions to the relationship between social capital[1] and economic development, there is a growing body of literature which considers the implication of social trust on economic performance. Social trust works mainly via two functions: they reduce information asymmetries and mitigate opportunistic behaviors (Arrow 1974; Flammer 2018). Both of these two functions can lower the market frictions which arise due to the difficulties to enforce contracts, which in turn affects the propagations of macroeconomic shocks.[2] However, little evidence has been provided about the link between social trust and macroeconomic shocks.

In this paper, we investigate whether social trust affects i) firms' access to trade credit under uncertainty in emerging market economies (EMEs) and ii) firms' performance under uncertainty in the context of profitability.[3] We focus on uncertainty shocks in EMEs for two reasons. First, the high level of uncertainty in EMEs[4] has been increasingly recognized important in forecasting economic fundamentals.[5] For example, Gourio et al. (2016) find that aggregate uncertainty is negatively associated with GDP, consumption, investment, etc. The existing studies demonstrate the impact of uncertainty from a macroeconomic perspective. The effect of aggregate uncertainty at the firm level, however, is rarely discussed in these countries. Next, emerging countries display less developed financial systems, which in turn amplifies the impact of uncertainty shocks via the credit channel (e.g., Carrière-Swallow and Céspedes 2013). Thus, the informal financing channel, such as trade credit, plays a vitally important role in firms' financial decisions in emerging countries. Social trust is critical for firms' incentives to extend trade credit. For instance, Wu et al. (2014) show that firms in provinces with higher levels of social trust tend to provide more trade credit to their customers in China. Social trust may affect the impact of uncertainty on firms' performance via the trade credit channel.

[1]In Putnam's (1993) argument, the society with a high level of social capital has a greater social trust. And a higher level of social capital is associated with a higher level of economic development.

[2] For example, Gete and Melkadze (2018) find that the aggregate volatility (uncertainty) shocks can be amplifies by a financial accelerator adopted from Bernanke et al. (1999).

[3]In this paper, firms' profitability equals the ratio of earning before interest and taxes to total sales.

[4]Bloom (2014) documents that developing countries tend to have a higher level of uncertainty. The concept of emerging and developing countries is not equal. But all the countries contained in our sample belong to developing countries other than South Korea and Singapore.

[5]The transmissions of uncertainty shocks in EMEs are a little different from that in developed countries. For example, Carrière-Swallow and Céspedes (2013) find that emerging countries suffer much more severe falls in investment and private consumption in response to an exogenous global uncertainty shock compared to the U.S. and other developed countries.

Trade credit, allowing customers to purchase goods and service without immediate payments, plays a vital role in many forms of transactions. According to the estimations of the Bank for International Settlements (2014), trade credit implements two-thirds of global trade around the world. Based on the existing studies, the impact of uncertainty shocks on trade credit is ambiguous. On the one hand, firms may receive trade credit because their suppliers want to keep a long-lasting relationship with them (e.g., Cunat 2001) or to reduce transaction costs (e.g., Ferris 1981). The strong relationship will become more valuable, and the transaction cost will increase with an increase in aggregate uncertainty. If this is the case, firms can receive more trade credit from their suppliers in response to uncertainty shocks. On the other hand, the suppliers bear the risk that their customers will not be able to repay the trade credit debt in the future. An increase in uncertainty will intensify the risk. This implies that the suppliers will have fewer incentives to provide trade credit. The net impact of uncertainty shocks on firms' access to trade credit depends on which effect dominates.

No matter which effect works, higher levels of social trust will help firms to obtain more trade credit under uncertainty. As with the former effect, firms in countries with higher levels of trust can get more trade credit because their suppliers are more likely to think they are trustworthy. For the latter effect, greater social trust can mitigate the suppliers' concern that their customers won't comply with their promise, and thus, won't reduce the provision of trade credit that much. Combining the two arguments above, we predict that social trust facilitates the use of trade credit when the aggregate economy suffers a positive uncertainty shock.[6]

The use of trade credit, however, always involves general equilibrium effects. The negative impact of uncertainty on trade credit could be due to either suppliers' unwillingness to extend trade credit or customers' decreasing demand for such credit. A lot of research (e.g., Peterson and Rajan 1997) on trade credit presupposes that firms will take on any credit offered to assume away this problem. Under this presupposition, the use of trade credit will depend on the suppliers' willingness. In our analyses, at first, we follow this presupposition. Then, we relax this presupposition and assume that firms with relatively high levels of liquidity needs will take on any credit offered. We infer that high-liquidity-needs firms in countries with higher levels of social trust could receive more trade credit in

[6] In some country with a very high level of social trust, firms' trade credit received will even increase because social trust can reduce the second effect in large amounts and increase the use of trade credit to substitute formal channels.

response to uncertainty shocks than similar firms in countries with lower levels of social trust.

We test our predictions by using a sample of firm-level data across 26 emerging countries over the years from 1995 through 2013. We use the standard deviation of daily stock market return as the index of uncertainty for the corresponding country. Following La Porta et al. (1997), we measure social trust by computing the ratio of the respondents who think "*most people can be trusted*" in response to the question "*Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?*" in the World Value Survey. This survey is conducted almost every five years after 1990. We extend this data to annual frequencies by letting the yearly value of social trust be identical to the value of the corresponding wave. In our empirical analyses, more firm-level characteristics and country-level factors are controlled.

We find that the key term, the interaction of uncertainty and social trust, enters positively and is significant at the 1% level. This implies that firms use more trade credit if they are in countries with higher levels of social trust with an increase in aggregate uncertainty. It is meaningful to understand the economic magnitude. To see this, we consider a hypothetical "low-trust" country with social trust equal to the 25% quantile (17.6) and a hypothetical "high-trust" country with social trust equal to the 75% quantile (32.5). With a one-standard-deviation increase in aggregate uncertainty, compared to firms in the low-trust country, the growth rate of account payable experiences a 3.58-percentage-point ((32.5-17.6)*0.24) smaller contraction for firms in the high-trust country. This magnitude (3.58) corresponds to 14.4% of the mean value of the growth rate (24.81). Building on this analysis, we then explore whether the relationship between social trust and trade credit is heterogeneous across industries. As trade credit is a type of short-term liquidity resource, its impact should be more apparent in industries that highly depend on liquid funds. We follow Raddatz (2006) to construct two measures of industry-level liquidity needs. We find that no matter which measures of liquidity needs are used, social trust has a significantly larger impact in the high-liquidity-needs industries. In detail, in the high-liquidity-needs group, with a one-standard-deviation increase in aggregate uncertainty, the growth rate of account payable experiences a 5.36-percentage-point smaller contraction for firms in the high-trust-country. The economic magnitude is larger than that of firms in the low-liquidity-needs group.

In addition to the informal financing channel, does social trust also encourage firms in EMEs to obtain financing via the formal channel, such as issuing debt or equity in face of a positive uncertainty shock? To address this question, we compute the growth rate of total debt and equity and use them as the dependent variables, respectively. We find that social trust doesn't have significant effects on firms' access to equity or debt with an increase in aggregate uncertainty. Even if we divide our sample into two subsamples based on the industry-level liquidity needs, none of the coefficients on the interaction of uncertainty and social trust are significant even at the 10% level. From this perspective, social trust mainly affects firms' performance through the trade credit channel rather than through raising more debt or issuing more equity that depends more on formal legal arrangements.

Firms adjust their formal and informal finance to keep their excellent performance. Depending on the relationship between social trust and firms' financing channel in EMEs, does social trust also affect the impact of uncertainty on firms' performance? We use firms' profitability as the representative to explore the relationship between social trust and firms' performance in face of uncertainty shocks. We find that social trust can actually facilitate firms' profitability when the aggregate economy suffers an increase in uncertainty as expected. Furthermore, consistent with the analyses on trade credit, firms in the high-liquidity-needs group will benefit more from the higher level of social trust.

## 2.2 Literature Review

Our paper contributes to the literature studying the impact of social trust in economic life. The literature can be divided into two parts: the impact of social trust from the macroeconomic perspective, such as economic development, and the impact on areas of corporate finance. Our work belongs to the latter part. Levine et al. (2018) use the same measure of social trust, but investigate its impact during banking crisis. They find that firms with higher levels of liquidity dependence suffer small declines in employment and profit in the presence of banking crisis, if they are in the high-trust countries, because they can get more trade credit than the firms located in the low-trust countries. Lins et al. (2017) use a different measure called corporate social responsibility (CSR) intensity and find that firms with higher social capital had higher stock returns during the 2008-2009 financial crisis. Different from their view that social trust works during periods of crisis, we find that social trust can affect the transmissions of uncertainty shocks in emerging countries. As for the relationship between social trust and economic development, other than Putnam's (1993) work we mentioned, La Parta et al. (1997) and Knack and Keefer (1997) provide strong evidence that trust and civil cooperation significantly affect aggregate economic activities.

Our paper complements the recent emerging literature on the relationship between uncertainty and corporate finance. Gulen and Ion (2016) use the economic policy uncertainty (EPU) index from Baker et al. (2016) to document a strong negative relationship between firm-level investment and aggregate uncertainty, and this negative relationship is even significant stronger for firms with higher irreversibility or government spending dependence. Kim and Kung (2017) use economic and political events as shocks to economic uncertainty, and find that firms with less re-deployable capital reduce investment more. This result still holds if they use VIX or EPU instead. Nguyen and Phan (2017) and Bonaime et al. (2018) explore the impact of aggregate uncertainty on mergers and acquisitions (M&A). They both find that an increase in aggregate uncertainty will decrease activities related to M&A. We differ these papers mainly from two perspectives. First, our research concentrates on emerging countries. Second, we argue a new channel to affect the impact of uncertainty on corporate finance: social trust.

## 2.3 Data

This paper focuses on the impact of social trust on the transmissions of uncertainty shocks in emerging countries. Our sample countries include Argentina, Brazil, Chile, Columbia, Egypt, Hungary, India, Indonesia, Korea, Morocco, Mexico, Malaysia, Nigeria, Pakistan, Peru, Philippine, Poland, Romania, Russia, Singapore, Thailand, Turkey, Ukraine, Venezuela, Vietnam, and South Africa. We choose these countries based on the following standards. First, the country belongs to emerging countries according to Emerging Market Bond Index (EMBI) operated by J.P. Morgan. Second, we can find its social trust in the World Value Survey (WVS) for at least one wave. Third, the country selected contains at least five firms, and each firm has at least three observations in the Compustat-Global. Fourth, we can find the country's index of uncertainty proxied by the yearly standard deviation of daily return in Baker et al. (2018). Fifth, in this paper, we control for some country-level macroeconomic variables, for example, the capitalization of the stock market, other than uncertainty and social trust. Thus, we should find these country-level variables in the World Bank dataset and Penn World Table. In this paper, we exclude China because a considerable number of China's publicly listed firms are state-own enterprises (SOEs) and they are highly regulated by the government. Besides, some countries listed above don't have the variable used in the robustness check. We will describe these situations in detail in the section of robustness.

After choosing the countries we used in the sample, we then get the corresponding firm-level data in the manufacturing sector (SIC 2000-3999) from the Compustat-Global. The sample of firms is restricted based on two standards. First, our sample periods extend from 1995 to 2013. Our sample starts in 1995 because one of our control variables, capital control, begins in 1995. We restrict our sample by 2013 because the index of uncertainty ends in 2013. Second, to reduce the effects of possibly spurious outlines, we follow a conventional procedure by eliminating the top and bottom 1% value of every firm-level variable, both dependent and explanatory variables included, to clean the data and prevent extreme outliers from driving the results.

In conclusion, the selection criteria end up with a sample of 5,336 firms, adding up to 47,877 firm-year observations. Each firm on average has almost nine observations.

### 2.3.1 Social Trust and Uncertainty Measure

We construct the measure of social trust based on the World Value Survey (WVS). The WVS contains one thematic subsection called social capital, trust and organizational membership which aims to inspect "People's beliefs, values and motivations" across countries over 6 waves.[7] Depending on the WVS, we construct the measure of social trust according to the answer to the following survey question:

*Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?*

People who are selected to participate this survey choose one response from three possible choices: i)Most people can be trusted; ii)You can't be too careful in dealing with people; iii)I have no answer. Following La Porta et al. (1997) and Levine et al. (2018), the index of social trust within one country in the corresponding wave is measured by the ratio of respondents whose answer is "Most people can be trusted" over the total respondents.

As our firm-level data is at the yearly frequency, we transform the measure of social trust into annual ones to match the analyses. Given the view that there exists strong persistence in social trust (e.g., Williamson 2000; Bilodeau and White 2016), we assume that the annual value of social trust is identical to its value in the corresponding wave. For example, social trust in 1998 for Argentina is equal to the value of social trust of the wave 1995-1998 in Argentina. As is shown in Table 2.1, the mean and median of social trust are 23.3 and 24.48, respectively, with a standard deviation of 11.16. Figure 2.1 shows the average value of social

[7]The 6 waves are 1981-1984, 1990-1994, 1995-1998, 1999-2004, 2005-2009, 2010-2014.

Table 2.1
**Statistical Descriptions**

| | Mean | Min | Max | Median | S.D. |
|---|---|---|---|---|---|
| **Dependent Variable** | | | | | |
| growth of Account Payable (%) | 24.81 | -99.01 | 755.21 | 7.65 | 81.29 |
| Account Payable (changes)/Costs (%) | 1.08 | -97.29 | 52.39. | 0.82 | 10.62 |
| Debt growth (%) | 22.41 | -100 | 1328.69 | 2.34 | 102.23 |
| Equity growth (%) | 12.81 | -66.82 | 431.31 | 0.33 | 45.10 |
| Profitability (%) | 7.61 | -129.33 | 60.38 | 7.62 | 14.11 |
| **Independent Variables** | | | | | |
| social trust | 24.56 | 3 | 52.1 | 23.3 | 11.24 |
| uncertainty | 0.015 | 0.0045 | 0.042 | 0.015 | 0.0055 |
| **Other controls** | | | | | |
| Size | 7.67 | 2.67 | 15.87 | 7.10 | 2.77 |
| Return on Asset | 0.098 | -0.27 | 0.37 | 0.097 | 0.085 |
| Book Leverage | 0.38 | 0 | 1.71 | 0.38 | 0.26 |
| Inventory/Total Asset (%) | 15.60 | 1.82 | 31.00 | 15.95 | 4.00 |
| Cash Conversion Cycles | 93.59 | 27.69 | 201.34 | 90.64 | 29.93 |
| GDP per capita (log) | 8.86 | 6.01 | 11.19 | 8.46 | 0.97 |
| Financial Development | 54.99 | 8.07 | 146.17 | 44.52 | 31.24 |
| Stock Market Capitalization | 68.60 | 0.41 | 250.71 | 61.69 | 44.22 |
| Growth of Broad Money (%) | 8.72 | -123.90 | 56.53 | 8.83 | 11.29 |
| Capital Control | 0.72 | 0 | 1 | 0.88 | 0.29 |
| Creditor Rights | 2.08 | 0 | 4 | 2 | 0.69 |
| Anti-self-dealing | 0.58 | 0.08 | 1 | 0.58 | 0.18 |

trust for each emerging country in our sample. We can see there exist a substantial variation of social trust across emerging countries. Among all emerging countries contained in our

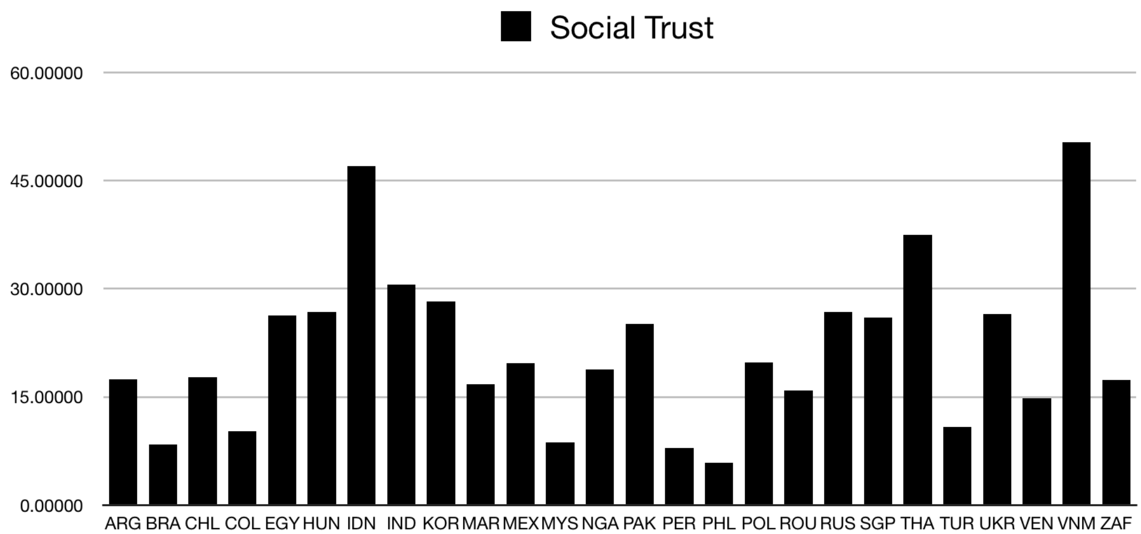



Figure 2.1: Social Trust
This figure presents the average value of social trust for the 26 emerging countries covered in our sample.

sample, Philippine has the low mean value of social trust, 5.89, whereas Vietnam has the highest mean value of social trust, 50.7.

In our framework, the changes in uncertainty are the driving force for the adjustment of corporate financial decisions and thus their outcome. An appropriate measure of uncertainty is vitally important for our analyses. In some influential work (e.g.,Bloom 2009), stock market volatility is thought as a suitable measure. This measure is simple and available for a very long period, free of revisions and sample selections. Baker et al. (2018) show that this measure is highly correlated other measures of both micro- and macro- level uncertainty, including cross-sectional firm return, bond yield, exchange rate, and forecaster disagreement. In emerging economy studies, this measure is also prevalent. Gourio et al. (2015) use this measure and find that it hurts net capital inflows. In our benchmark analyses, we borrow the data, cross-country realized stock return standard deviation, from Baker et al. (2018) which in turn rely on Global Financial Data (GFD). Their data is at the quarterly frequency, and we transform it into annual frequencies by computing the arithmetic mean of the corresponding year for each country. We lag this annual index for one year. Table 2.1 reports that the median and mean of uncertainty are both 0.015 with a standard deviation of 0.0055. In the results we report, we normalize this index to 0 mean and unit standard deviation.

### 2.3.2 Trade Credit Financing

In this paper, we want to emphasize the role of trade credit when the aggregate economy suffers an increase in uncertainty. Our primary variable of interest is accounts payable (*ap*) which captures the amount of services and goods the customer can receive in advance without immediate payments. This variable is a stock entry on firms' balance sheet and can be seen as the total amount of trade credit firms obtain from their suppliers. Thus, the amount of financing through trade credit equals the change in accounts payable during a particular period (Levine et al. 2018). Firms' financing through trade credit is positive if they obtain more goods and services than the sum of what they pay and the pay-down of the stock of account receivable, whereas it becomes negative otherwise. We scale firms' trade credit financing by the account payable at the beginning of the corresponding period, and use this ratio as the dependent variable. We can understand this ratio as the growth rate of accounts payable/trade credit received. The descriptive statistics of the growth rate of trade credit is reported in Table 2.1. We can see that the median and mean of the growth rate are 7.7% and 24.8%, respectively, with a standard deviation of 0.81.

### 2.3.3 Other Firm-level Variables

Trade credit is often thought of as an informal type of firms' financing. In this paper, to further understand the impact of social trust on firms' financing behaviors when they are in face of an increase in uncertainty, we also examine two measures of formal financing, issuing debts and equity. As with the former variable, we calculate the total amount of debt by adding short-term debt (*dlc*) and long-term debt (*dltt*). These two items are also stock entries on firms' balance sheet. To be consistent with our analyses on trade credit, we use the changes in total debt scaled by the total debt at the beginning of the corresponding period, i.e., the growth rate of total debt, as the dependent variable. The descriptive statistics of this variable are reported in Table 2.1. The median and mean values of the growth rate of total debt are 2.34% and 22.42%, respectively, with a standard deviation of 1.02. As with equity issuance, we construct it based on Baker et al. (2003). First, we compute the stock of equity issued by adding the common/ordinary equity (*ceq*) and deferred taxes (*txdb*) but minus retained earnings (*re*). The new issuance of equity thus equals the changes of the stock during one period. Still, in line with trade credit and debt, we scale the new equity issuance by the stock value of equity at the beginning of the corresponding period. The new dependent variable is the growth rate of equity issued in essence. We also summary this dependent variable in Table 2.1. The mean and median values are 0.33% and 12.81%, respectively, with a standard deviation of 0.45.

Firms adjust their financing behaviors to foster their outcome or performance. To explore whether social trust plays a vital role in the impact of uncertainty on firms' performance, we use firms' profitability as a representative of firms' performance. Here, we follow the common practice to define firms' profitability as the ratio of earnings before interest and taxes (*ebit*) over total sales (*sale*). We repeat the regressions by using this ratio as the new dependent variable. The mean and median values of this ration are both 7.6%, with a standard deviation of 0.15, as is reported in Table 2.1.

Several time-varying firm-level characteristics are considered to have impacts on firms' incentives to offer trade credit, debt and equity issuing, and thus firms' profitability. Hence, these variables should be included as controls in all regressions. First, firms with different sizes may have different financing strategies, and thus the trade credit received is affected. We control for firms' size which is measured by the logarithm of total assets (*at*). Second, we also include return on assets to capture firms' differences in generating earnings and implementing efficient management. It is measured by the ratio of operating income before depreciation (*oibdp*) to total assets. Third, to control for the effect of firms' capital structures on trade credit, we include the book leverage ratio in our regressions. Here we follow Alfaro et al. (2018). It is computed by the ratio of the total debt (the sum of short-term debt (*dlc*) and long-term debt (*dltt*)) to the sum of total debt and common/ordinary equity (*ceq*). The statistical descriptions of these controls are also present in Table 2.1.

### 2.3.4 Industry-level Liquidity Needs

In our central part of analyses, we build on our benchmark results to test an additional implication that the impact of social trust is heterogeneous across different industries with different external liquidity needs. Some industries rely on liquid funds more due to some technical reasons, such as the long production process. Durable good sectors usually have higher levels of reliance on the availability of liquid funds than the nondurable sectors. Firms in those industries with relatively high levels of external liquidity needs may have higher demands for trade credit from their suppliers, and thus social trust may have more substantial impacts.

We follow Raddatz (2006) and use the data from Compustat-U.S. to construct the measure of liquidity needs. We use U.S. data because the U.S. has one of the most developed markets in the world, and the variation in liquidity needs across industries mainly reflects the technical differences in demands for liquid funds (Rajan and Zingales 1998). In our analyses, we proxy liquidity needs by the ratio of inventories (*invt*) to total sales (*sale*). The construction process is as follows. First, we calculate the sum of firms' inventories and sales over the relevant periods, and then computes the ratio of inventories to total sales. Second, we use the median level of the distribution of this ratio within the corresponding industry as the industry-level liquidity needs. In this paper, we divided manufacturing firms into 127 industries based on the three-digit SIC code. In our exercise, we restrict the sample from 1979 to 1995 because the sample we use in the regressions starting from 1995. If the sample is extended to 2013 and we construct the measure following the same procedures, we find that the former measure is highly correlated with the latter one. The summary statistics of industry-level liquidity needs are reported in Table 2.1. The mean and median values of this variable are 0.16 and 0.17, respectively, with a standard deviation of 0.04. The industry group, newspapers: publishing or publishing and printing (SIC code 271) has the lowest value of liquidity needs, 0.018, whereas the industry group, musical instruments (SIC code 391) depends on liquid fund most with the highest liquidity needs, 0.31.

There is a concern that our results are just driven by the particular measure of industry-level liquidity needs we use. To address this concern, we follow Richards and Laughlin (1980) to construct another measure of industry-level liquidity needs, the cash conversion cycles, to check the robustness of our results in our analyses. This measure corresponds to the sum of the average age of inventories, the average age of accounts payable, and minus the average age of accounts payable (inventories (*invt*)/cost of goods sold (*cogs*)*365 + accounts receivable (*rect*)/sales (*sale*)*365 - accounts payable (*ap*)/cost of goods sold (*cogs*)*365). Richards and Laughlin (1980) document that this measure reflects the periods one firm needs to convert a dollar of cash disbursements back into a dollar of cash inflow from its regular course of operations. The longer the time is required, the more one firm depends on liquid funds. The cash conversion cycles are highly correlated with the ratio of inventories over total sales ($corr(cycles, ratio) = 0.87$). The mean and median time to convert the cash disbursement is 93.6 and 90.6 days, respectively, with a standard deviation of 39.9. The industry group, petroleum refining (SIC code 291), has the lowest cash conversion time, 27.7 days,[8] whereas the industry group, musical instruments (SIC code 391), needs 201.3 days to convert a

[8]The corresponding ratio of inventories over total sales for petroleum refining industry is 0.086, ranking 10th among all the 127 manufacturing industry groups. Thus, we can say that petroleum still belongs to the low liquidity need industry in term of the ratio of inventories to total sales. At the same time, The industry group, newspapers: publishing or publishing and printing (SIC code 271), needs 34 days to convert a dollar of cash disbursements back into a dollar of cash inflow. This time periods rank 5th among all the 127 industry groups, implying that the corresponding industry belongs to the low liquidity need industry in term of the cash conversion cycle.

dollar of cash disbursements back into a dollar of cash inflow. Thus, the musical instrument industry is the one depending on liquidity most, whether from the perspective of the ratio of inventories over sales, or the cash conversion cycle. Finally, in the Appendix, we use another measure, the ratio of short-term debt (*dlc*) to total sales (*sales*), to recheck the robustness of our results. This measure captures one firm's ability to pay its current liabilities out of ongoing income.

### 2.3.5 Country-level Controls

In this paper, the main concern of our analyses is that our results may just capture the aggregate time trend that is common to all firms in the corresponding country but potentially affect the trade credit received. For instance, firms may receive more trade credit if the financial markets of the corresponding country become loosen. To address this omitted variable bias concern, we control for possible lurking macroeconomic factors that may affect firms' access to trade credit explicitly. First, to control for the impact of economic development, we add the natural logarithm of time-varying GDP per capita in the regressions. GDP per capita equals real GDP divided by population according to its definition. We obtain the latter two variables from the Penn World Table 9.0.[9] Second, A large body of financial literature documents that the development of financial intermediaries and markets is vitally important for firms' financing behaviors as well as economic performance (e.g., Levine et al. 2000 and Hsu et al. 2014). We add two variables denoting the development of financial institutions and stock market respectively in our regression equations. The financial institution development is indexed by the ratio of private credit by banks and other financial institutions over GDP, while the stock market development is indexed by stock market capitalization divided by GDP. Third, we use the growth of liquid liability (broad money) to denote countries' time-varying liquid conditions. Those variables mentioned in the second and third steps come from Global Financial Development operated by the World Bank. Finally, our research concentrates on the interaction of social trust and uncertainty in emerging countries. These countries usually implement capital control policies to restrict the cross-border free capital flow. Thus, we control for the factor representing capital controls. This variable is from Fernandez et al. (2016). The summary statistics of the macroeconomic variables are reported in Table 2.1. Some literature shows that country-level characteristics can also affect the transmissions of macroeconomic shocks. For example, Aghion et al. (2009) provide some evidence that the level of financial development affects the impact of real exchange rate volatility on productivity growth. To isolate their impacts on the trans-

[9]Real GDP here refers the expenditure-size real GDP at chain PPPs.

missions of uncertainty shocks, we interact the proxy for uncertainty with the country-level characteristics to see whether our results are robust.

Besides the country-level variables mentioned above, one concern in our analysis is that the high-level social trust may be just a result of the high economic quality, effective legal systems in enforcing contracts, high trust in government or the good protection of creditors and shareholders. To exclude the impact of these factors, we should add the interaction of uncertainty with the overall level of economic institution, the effectiveness of the legal system in enforcing contracts, the level of people's confidence in their government, and the degree to which the formal legal system protects creditors and shareholders in our robustness check analyses, respectively. The country-level variables mentioned above are obtained from various sources. The overall level of economic institution comes from Kunčič (2014). The index of the legal system is obtained from the Worldwide Governance Indicator operated by the World Bank. We construct people's confidence according to WVS from the answer to the following question:

*I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: is it a great deal of confidence, quite a lot of confidence, not very much confidence or none at all?*

We use the ratio of the respondents whose answers are "a great deal of confidence" or "quite a lot of confidence" to the total respondents as the measure of people's confidence in the government. The creditor rights index is constructed by Djankov et al. (2007) based on countries' bankruptcy and reorganization law, and it can reflect the degree to protect creditors from the perspectives of opinion voicing, getting repaid and affecting the reorganization. The anti-self-dealing index is a measure reflecting the extent to which the legal systems can protect minority shareholders against expropriation by corporate insiders. We obtain this index from Djankov et al. (2008).

## 2.4 Empirical Strategy

This section presents our baseline analyses. We start by examining whether social trust affects the transmission of uncertainty shocks via the trade credit channel in EMEs. We also exploit industry-level liquidity needs to check the heterogenous effects of social trust. Next, we provide four robustness checks to our baseline results. Third, we extend our analyses to two formal credit channels: debt and equity. Finally, we use firms' profitability as the representative to test how social trust affects firms' performance under aggregate uncertainty.

### 2.4.1 Social Capital, Aggregate Uncertainty and Trade Credit Financing

Existing studies show that uncertainty shocks have large impacts on firms' performance. For example, Gulen and Ion (2016) find a strong negative relationship between economic policy uncertainty and firm-level investment. These negative effects can be mitigated by asset re-deployability (Kim and Kung 2017). Besides, Lins et al. (2017) document that firms with greater social trust suffer smaller drops in stock return, profitability, growth, and sales per employee during the 2008-2009 financial crisis. In this subsection, we combine the discussions of social trust and uncertainty shocks together, and test how social trust affects the transmissions of uncertainty shocks to firms' trade credit in emerging countries. The main empirical specification is as follows:

$$tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1}$$

$$+\beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t} \qquad (1)$$

where $tcgr_{i,c,t}$ refers to the growth rate of trade credit received by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the value of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics, such as firm size, in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g., GDP per Capita, Financial Development and Capital Account Openness).

Time fixed effects, $u_t$, are included in the regressions to capture the global time trend that is common to all firms but potentially affects firms' access to trade credit. For instance, firms are less likely to receive trade credit from the multinational suppliers in response to a global contraction shock, such as US monetary recession shocks. Lin and Ye (2018) provide robust evidence that global liquidity shocks can affect firms' incentives to provide trade credit to their customers even if there exist tight capital controls. Meanwhile, we also include firm fixed effects ($u_i$) to control for time-invariant unobservable firm characteristics which may influence firms' ability to receive trade credit. For example, The firms in our sample come from different emerging countries, and various countries have various legal systems which can affect the implementation of the trade credit contract. Firms from countries with imperfect

Figure 2.2: **Social Trust, Uncertainty and Trade Credit**

Total Sample

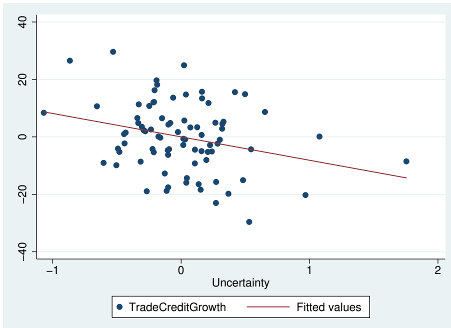



Figure 2.2(a)

Total Sample

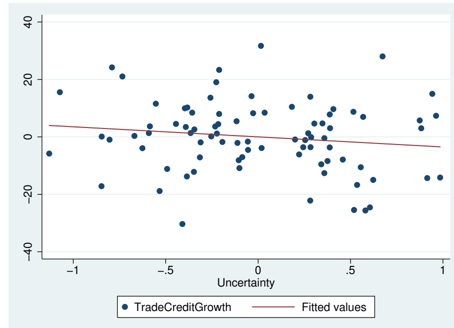



Figure 2.2(b)

This Figure shows the relationship between aggregate uncertainty and trade credit received. We use the total sample and calculate the country-year mean of firm size, return on asset, book average and the trade credit growth rate. We call the country-year observations whose social trust is in the upper quantile the high trust countries (Figure 2.2(b)) and the observations whose social trust is in the lower quantile the low trust countries (Figure 2.2(a)). The X-axis is the index of uncertainty and the Y-axis represents trade credit. We exclude firm size, return on asset, book leverage, macroeconomic vectors, country- and time- fixed effects from uncertainty and trade credit received.

legal systems are likely to receive less trade credit from their suppliers. For example, Li, Zhou, Du and Zhao (2018) find that sound legal systems facilitate the provision of trade credit significantly in emerging economies. Furthermore, to exclude the effects of law on the transmissions of uncertainty shocks, we add the interaction of uncertainty and the rule of law to check the robustness. This will be discussed in detail in the robustness check. Standard errors are clustered at the country level in our baseline analyses. If we cluster standard errors at the country and year level, our results keep their significance. We present the results in Appendix A2.1.

We are interested in the interaction term of uncertainty and social trust, $Trust_{c,t} * Uncertainty_{c,t-1}$. The estimated coefficient on the interaction term, $\beta_1$, captures the differential responses to positive uncertainty shocks for firms from countries with different levels of social trust. We expect that social trust facilitates firms' access to trade credit during periods of high uncertainty. Thus, a positive coefficient, $\beta_1$, supports our prediction.

We first present some preliminary visual results in Figure 2.2. We construct two subsamples. One is the high-trust group whose social trust is in the upper quantile, whereas

Figure 2.3: **Social Trust, Uncertainty and Trade Credit**

The High-liquidity-needs Group

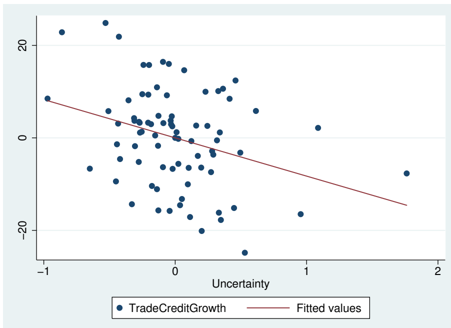



Figure 2.3(a)

The High-liquidity-needs Group

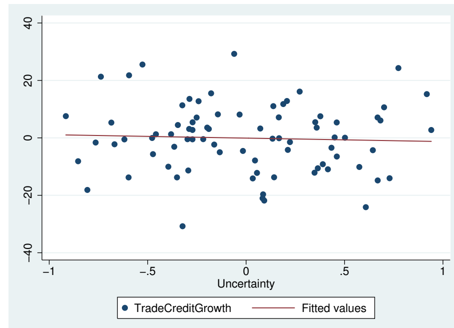



Figure 2.3(b)

The Low-liquidity-needs Group

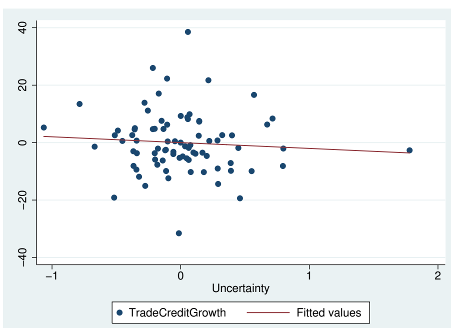



Figure 2.3(c)

The Low-liquidity-needs Group

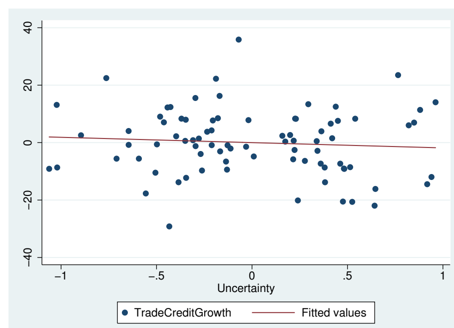



Figure 2.3(d)

**Low Social Trust Countries** **High Social Trust Countries**

This Figure shows the relationship between aggregate uncertainty and trade credit received. We divide our sample into two subsamples based on industry-level liquidity needs. The observations whose liquidity needs are above the median are assigned into the high-liquidity-needs group and others are in the low-liquidity-needs group. For each group, we calculate the country-year mean of firm size, return on asset, book average and the trade credit growth rate. We call the country-year observations whose social trust is in the upper quantile the high trust countries (Figure 2.3(b) and 2.3(d)) and the observations whose social trust is in the lower quantile the low trust countries (Figure 2.3(a) and 2.3(c)). The X-axis is the index of uncertainty and the Y-axis represents trade credit. We exclude firm size, return on asset, book leverage, macroeconomic vectors, country- and time- fixed effects from uncertainty and trade credit received.

Table 2.2
**Benchmark Results**

| | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.24*** | 0.39*** | 0.12** | 0.33*** | 0.17*** |
| | (0.065) | (0.099) | (0.056) | (0.093) | (0.056) |
| Uncertainty | -6.67*** | -9.50*** | -4.50** | -8.32*** | -5.38*** |
| | (2.14) | (3.22) | (1.72) | (2.96) | (1.75) |
| Trust | -0.16 | -0.036 | -0.32** | 0.042 | -0.37** |
| | (0.14) | (0.19) | (0.13) | (0.19) | (0.13) |
| Fixed Effect | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,782 | 24,133 | 23,649 | 24,834 | 22,948 |
| Firms | 5,323 | 2,714 | 2,609 | 2,790 | 2,533 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 9.48*** | | 4.55** | |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the high-liquidity-needs group, and Column (iii) and (v) show the results on the results on the low-liquidity-needs group. Here, the high group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

the other is the low-trust group whose trust is in the lower quantile. Figure 2.2(a) presents the relationship between aggregate uncertainty and the country-year mean of trade credit financing in the low-trust group, and Figure 2.2(b) presents the high-trust group. We can see that in the low-trust group, trade credit declines more as uncertainty increases, which is in line with our conjecture.

The estimation result is shown in the first column of Table 2.2. We can see that the coefficient on the interaction of uncertainty and social trust is positive and statistically significant at the 1% level. That is to say, with an increase in aggregate uncertainty, firms use more trade credit if they are in emerging countries with higher levels of social trust. A lot of literature has documented that country-specific characteristics, such as financial development and capital account openness, can affect the transmission of macroeconomic shocks. To isolate the effects of these country characteristics, we interact the index of uncertainty with these variables, and add them in equation (1). The result is present in the Appendix A2.2. Adding those interactions doesn't alter the sign and significance of the coefficient on the interaction term of uncertainty and social trust. For a similar reason, we also add the interactions of uncertainty and firm-level controls in equation (1) to exclude the impact of firm-level characteristics, such as firm size. The benchmark result still holds, and we show these results in the Appendix A2.3.

It is meaningful to understand the economic magnitude. To see this, we consider a hypothetical "low-trust" country with social trust equal to the 25% quantile (17.6) and a hypothetical "high-trust" country with social trust equal to the 75% quantile (32.5). With a one-standard-deviation increase in the index of uncertainty (proxied by the one-year lagged yearly standard deviation of the daily stock return), compared to firms in the low-trust country, firms in the high-trust country suffers a 3.58-percentage-point ((32.5-17.6)*0.24) smaller contraction in the growth rate of account payable. This magnitude (3.58) corresponds to 14.4% of the mean value of the growth rate (24.81).

Building on the regression result of equation (1), we then test additional implications of the point that social trust facilitates firms' access to trade credit when they suffer uncertainty shocks. Under this view, the impact of social trust on the transmission of uncertainty shocks is disproportionate. Firms which need more liquid funds will benefit more from the greater social trust. We test this prediction following three steps. First, we define the level of liquidity needs as the ratio of inventories scaled by total sales. We construct an industry-level index of liquidity needs following Raddatz (2006). Next, we divide the observations in our sample into two groups according to the index of industry-level liquidity needs. We call the group whose liquidity needs are above the median level the high-liquidity-needs group and the other group the low-liquidity-needs group. Third, we repeat the regression of equation (1), and see whether the coefficient on the interaction term, $\beta_1$, of the high group is significantly larger than that of the low group. To see whether our result is robust to a different measure of liquidity needs, we construct another measure, the cash conversion cycles, henceforth CCC, also following Raddatz (2006). The group with higher CCC needs more liquid funds. Then we repeat all the three steps described above. A larger coefficient on the interaction term, $\beta_1$, for the group with higher CCC is consistent with our prediction.

Also, we present some preliminary visual results in Figure 2.3. First, we divide our sample into two groups based on industry-level liquidity needs.[10] The observations whose liquidity needs are above the median are assigned into the high-liquidity-needs group, and others are in the low-liquidity-needs group. For each group, we construct two subsamples. One is the high-trust group whose social trust is in the upper quantile, whereas the other is the low-trust group whose trust is in the lower quantile. Figure 2.3(a) shows the relationship between aggregate uncertainty and trade credit for the group with high trust and high liquid needs, figure 2.3(b) for the group with low trust and high liquid needs, figure 2.3(b) for the group with low trust and low liquid needs, and figure 2.3(d) for the group with high trust and low liquid needs. We can see for the high-liquidity-needs group, firms in the high-trust countries obtain more trade credit than similar firms in the low-trust countries.

We show the regression results in the last four columns of Table 2.2. In column (ii) and (iii), we use the ratio of inventories to sales as the index of liquidity needs. They provide the results of the high-liquidity-needs group and the liquidity needs group, respectively. Column (iv) and (v) use CCC to index liquidity needs. Column (ii) and (iv) show that the coefficients on the interaction of uncertainty and social trust are positive and statistically at the 1% level among firms in the high-liquidity-needs group. This positive relationship between social trust and trade credit financing during periods of high uncertainty holds for either index of liquidity needs. We use the result in column (ii) as an example and still consider the firms in the low-trust and high-trust countries. When the aggregate economy experiences a one-standard-deviation increase in aggregate uncertainty, high-liquidity-needs firms in the high-trust country experiences a 5.81-percentage-point ((32.5-17.6)*0.39) smaller contraction than similar firms in the high-trust country. Furthermore, we find that the coefficients on the interaction term in the low-liquidity-needs group are smaller than those in the high-

[10] In Figure 2.3, we use the ratio of inventories to total sales as the measure of liquidity needs.

liquidity-needs group. The F-statistics imply that the coefficients on the interaction term between the two groups are significantly different at the 5% level. This finding is consistent with our prediction that firms which need more liquid funds benefit more from greater social trust in face of uncertainty shocks.

If we use the ratio of short-term debts to total sales as the measure of liquidity needs, our results still hold. We present them in the Appendix A2.4.

### 2.4.2 Robustness

In this section, we provide some sensitivity analyses to see whether our results are robust, if we add the interaction of uncertainty with some other country characteristics and use an alternative measure of uncertainty.

#### Other Channels

We come across several challenges to identify the impact of social trust on the propagations of uncertainty shocks to firms' access to trade credit. The first one is that the high social trust may be just a result of good economic institutions, effective legal systems in enforcing contracts, high trust in government, or the good protection of creditors and shareholders. If this is the case, our results may just reflect the impact of the other country-level characteristics which affect the transmissions of uncertainty shocks. To address this concern, we control for the interaction of uncertainty and the overall level of economic institution, the effectiveness of the legal system in enforcing contracts, the level of people's confidence in their government, and the degree to which the formal legal system protects creditors and shareholders, respectively. We use the following empirical specification:

$$tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t}$$

$$+\beta_4 * CC_{c,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t} \tag{2}$$

where $CC_{c,t} \in \{Institution_{c,t}, Law_{c,t}, GovTrust_{c,t}, CR_c, AntiSelf_c\}$. $Institution_{c,t}$ is the overall level of country $c$'s economic institution in period $t$. $Law_{c,t}$ measures the effectiveness of the legal system in enforcing contracts in the country $c$ during the year $t$. $GovTrust_{c,t}$ represent people's confidence in their government in year $t$ for country $c$. $CR_c$ denotes the strength of the legal rights of creditors. $AntiSelf_c$ reflects the degree to which the legal systems protects small investors from self-dealing by corporate insiders. Other variables are the same as those in equation (1).

Table 2.3
**Additional Controls I**

| **Panel A: Institution** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.32*** | 0.49*** | 0.21** | 0.46*** | 0.21** |
| | (0.088) | (0.12) | (0.075) | (0.12) | (0.081) |
| Uncertainty | -10.24*** | -14.44*** | -7.46*** | -14.18*** | -7.13** |
| | (3.42) | (5.02) | (2.51) | (4.81) | (2.33) |
| Trust | -0.16 | 0.080 | -0.46** | 0.12 | -0.49*** |
| | (0.20) | (0.29) | (0.16) | (0.30) | (0.15) |
| Uncertainty*Institution | 0.17 | 0.033 | 0.28*** | 0.12 | 0.20* |
| | (0.12) | (0.16) | (0.092) | (0.15) | (0.098) |
| Institution | -0.46* | -0.46 | -0.49** | -0.32 | -0.62** |
| | (0.24) | (0.36) | (0.20) | (0.37) | (0.23) |
| Observations | 34,723 | 17,426 | 17,297 | 17,910 | 16,813 |
| Firms | 4,628 | 2,348 | 2,280 | 2,407 | 2,221 |
| $R^2$ | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 |
| F-Stat($\beta_H - \beta_L = 0$) | | 7.95*** | | 7.00*** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table uses the following empirical empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \beta_4 * CC_{c,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $CC_{c,t} \in \{Institution_{c,t}, Law_{c,t}, GovTrust_{c,t}, CR_c, AntiSelf_c\}$. $Institution_{c,t}$ is the overall level of country $i$'s economic institution in period $t$. $Law_{c,t}$ measures the effectiveness of the legal system in enforcing contracts in country $c$ during year $t$. $GovTrust_{c,t}$ represent people's confidence in their government in year $t$ for country $c$. $CR_c$ denotes the the strength of the legal rights of creditors and $AntiSelf_c$ reflects the degree to which the legal systems protects small investors from self-dealing by corporate insiders. Other variables are same with those in Table 2.2. The column order of the regressions is same with those in Table 2.2. Column (i) provides the results on the full sample, column (ii) and (iv) provide the results of the high-liquidity-needs group, and column( iii) and (v) show the results of the low-liquidity-needs group. In panel A, we include the interaction of uncertainty and the overall level of economic institution to exclude the impact of institutional quality. Panel B exclude the impact of the effectiveness of the legal systems, Panel C the impact of people's confidence in their government, Panel D the impact of creditor right protections and Panel E the impact of the protection on shareholders. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Table 2.3 (Continue)
**Additional Controls II**

| **Panel B: Law** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.24*** | 0.37*** | 0.12* | 0.33*** | 0.15** |
| | (0.065) | (0.088) | (0.063) | (0.085) | (0.065) |
| Uncertainty | -6.54*** | -9.27*** | -4.36** | -8.08*** | -5.16** |
| | (2.10) | (2.72) | (1.99) | (2.59) | (2.03) |
| Trust | -0.096 | 0.036 | -0.25 | 0.16 | -0.35* |
| | (0.20) | (0.23) | (0.20) | (0.25) | (0.19) |
| Uncertainty*Law | 0.039** | 0.058*** | 0.022 | 0.055*** | 0.024 |
| | (0.018) | (0.014) | (0.022) | (0.019) | (0.018) |
| Law | 0.0034 | 0.045 | -0.034 | 0.036 | -0.023 |
| | (0.059) | (0.071) | (0.062) | (0.066) | (0.062) |
| Observations | 43,519 | 22,024 | 21,495 | 22,693 | 20,826 |
| Firms | 5,266 | 2,688 | 2,578 | 2,765 | 2,501 |
| $R^2$ | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |
| F-Stat($\beta_H - \beta_L = 0$) | | 10.60*** | | 5.84** | |
| **Panel C: Government Trust** | | | | | |
| Uncertainty*Trust | 0.22*** | 0.36*** | 0.13* | 0.32*** | 0.16** |
| | (0.075) | (0.11) | (0.064) | (0.11) | (0.060) |
| Uncertainty | -6.54*** | -9.41*** | -4.77** | -8.42** | -5.33*** |
| | (2.32) | (3.21) | (1.81) | (3.09) | (1.88) |
| Trust | 0.034 | 0.35 | -0.14 | 0.46** | -0.22 |
| | (0.16) | (0.22) | (0.15) | (0.20) | (0.16) |
| Uncertainty*GovTrust | -0.0036 | 0.063 | -0.056 | 0.051 | -0.056 |
| | (0.042) | (0.064) | (0.038) | (0.057) | (0.041) |
| GovTrust | -0.031 | 0.020 | -0.060 | 0.12 | -0.15 |
| | (0.22) | (0.25) | (0.20) | (0.23) | (0.22) |
| Observations | 46,521 | 23,452 | 23,069 | 24,171 | 22,350 |
| Firms | 5,251 | 2,671 | 2,580 | 2,751 | 2,500 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-Stat($\beta_H - \beta_L = 0$) | | 7.91*** | | 4.17** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 2.3 (Continue)

**Additional Controls III**

| **Panel D: creditor rights** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.23*** | 0.38*** | 0.12* | 0.31*** | 0.18*** |
| | (0.066) | (0.10) | (0.059) | (0.091) | (0.057) |
| Uncertainty | -6.61*** | -9.46*** | -4.39** | -7.95** | -5.56*** |
| | (2.17) | (3.23) | (1.81) | (2.87) | (1.75) |
| Trust | -0.12 | 0.0084 | -0.28 | 0.12 | -0.35** |
| | (0.16) | (0.21) | (0.14) | (0.23) | (0.14) |
| Uncertainty*CR | 0.82 | 0.92 | 0.78 | 1.83 | 0.054 |
| | (1.12) | (1.55) | (0.89) | (1.52) | (0.81) |
| Observations | 47,179 | 23,970 | 23,354 | 24,526 | 22,653 |
| Firms | 5,176 | 2,677 | 2,536 | 2,717 | 2,459 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 8.24*** | | 3.57* | |
| **Panel E: Anti-Self dealing** | | | | | |
| Uncertainty*Trust | 0.24*** | 0.38*** | 0.12* | 0.31*** | 0.18*** |
| | (0.066) | (0.092) | (0.060) | (0.087) | (0.058) |
| Uncertainty | -6.50*** | -9.03** | -4.53** | -7.67** | -5.58*** |
| | (2.11) | (2.94) | (1.77) | (2.76) | (1.74) |
| Trust | -0.15 | -0.027 | -0.31** | 0.049 | -0.36** |
| | (0.14) | (0.18) | (0.14) | (0.19) | (0.13) |
| Uncertainty*AntiSelf | 2.16 | 4.36 | 0.80 | 3.81 | 1.22 |
| | (3.41) | (4.81) | (3.31) | (4.39) | (3.32) |
| Observations | 47,500 | 24,020 | 23,480 | 24,727 | 22,773 |
| Firms | 5,244 | 2,682 | 2,562 | 2,760 | 2,484 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 9.95*** | | 4.05** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Also, we repeat all these robustness check regressions by assigning the firms into two different groups based on the measures of liquidity needs. In this way, we investigate whether the heterogeneous effects of social trust still hold after excluding other channels.

We report the results in Table 2.3. The column order of the regressions is the same as those in Table 2.2. Column (i) provides the results on the full sample, Column (ii) and (iv) provide the results of the high-liquidity-needs group, and Column( iii) and (v) provide the results of the low-liquidity-needs group. In panel A, we include the interaction of uncertainty and the overall level of the economic institution to exclude the impact of institutional quality. Panel B excludes the impact of the effectiveness of the legal systems, Panel C the impact of people's confidence in their government, Panel D the impact of creditor right protections, and Panel E the impact of the protection on shareholders.

We can see no matter which channel is excluded, the main results in the benchmark analyses still hold. First, the coefficients on the interactions of uncertainty and social trust are positive and significant at the 1% level, implying that social trust facilitates firms' access to trade credit with an increase in aggregate uncertainty in the EMEs. Second, the coefficients on the interactions between the high- and low-liquidity-need groups are significantly different at 10% level at least, and the coefficients of the high group are larger than those of the low group. Thus, firms which need more liquidity will benefit more with an increase in uncertainty, if they are in emerging countries with higher levels of social trust.

To gauge the economic magnitude, we use Panel A which excludes the impact of economic institutional quality as an example. We still take the high- and low-trust countries into account. With a one-standard-deviation increase in aggregate uncertainty, compared to those firms in the low-trust country, the growth rate of account payable experiences a 4.77-percentage-points ((32.5-17.6)*0.32) smaller contraction among firms in the high-trust country. This magnitude (4.77) equals 19% of the mean value of the growth rate (25.05). If the firms are in industries with higher levels of liquidity needs, the growth rate is 7.30 ((32.5-17.6)*0.49) percentage points larger among firms in the high-trust country.

**Other Measure of Uncertainty**

In this paper, we focus on the transmission of uncertainty shocks. An appropriate measure of uncertainty is vitally important in our empirical analyses. Other than the standard deviation of daily stock return, there are several other prevalent measures. The second concern

Table 2.4

**New Uncertainty Measure**

| | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.29** | 0.42*** | 0.20*** | 0.47*** | 0.16** |
| | (0.073) | (0.13) | (0.059) | (0.14) | (0.060) |
| Uncertainty | -5.04** | -7.27* | -3.65* | -8.98** | -2.44 |
| | (2.27) | (3.68) | (1.79) | (3.58) | (2.09) |
| Trust | -0.28** | -0.25 | -0.36** | -0.19 | -0.41*** |
| | (0.13) | (0.15) | (0.14) | (0.16) | (0.13) |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Observations | 39,738 | 19,885 | 19,853 | 20,706 | 19,032 |
| Firms | 4,446 | 2,260 | 2,181 | 2,355 | 2,086 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-Stat($\beta_H - \beta_L = 0$) | | 3.24* | | 5.20** | |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of cross-sectional firm-level stock return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the subsample of "High" liquidity need group and Column (iii) and (v) show the results on the results on the subsample of "Low" liquidity need group. Here the "High" group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

about our analyses is whether the results are robust to other measures of uncertainty. To address this concern, we use another measure of uncertainty, the standard deviation of quarterly returns across firms, to test the effects of social trust on the propagation of uncertainty shocks on firms' access to trade credit in EMEs. We call this measure micro uncertainty, and also repeat the regressions after dividing the observations into two subsamples based on liquidity needs.

We report the estimation results related to micro uncertainty in Table 2.4. The order of the regression is the same as in Table 2.2. Our regression results are robust to the new measure of uncertainty. First, the coefficient on the interaction of micro uncertainty and social trust is positive and statistically significant at the 5% level. That is to say, firms get more trade credit if they are in countries with higher levels of social trust with an increase in micro uncertainty. In detail, the growth rate of account payable experiences a 4.32-percentage-point ((32.5-17.6)*0.29) smaller contraction among firms in the high-trust country. Second, the coefficients of the high-liquidity-needs group are significant at the 1% level, and larger than that of the low group. Firms with higher levels of liquidity needs benefit more from the higher level of social trust in EMEs.

Do our results related to micro uncertainty still hold if we control for the impact of other channels, such as institutional quality? Furthermore, to exclude the effects of other channels, we control for the interaction of micro uncertainty and the overall level of economic institution, the effectiveness of the legal system in enforcing contracts, the level of people's confidence in their government and the degree to which the formal legal system protects creditors and shareholders, respectively. These results are shown in Appendix A2.5.

**Other Robustness Checks**

Finally, we are concerned that uncertainty may hurt social trust. If this were the case, it might hinder the effectiveness of our regression results from explaining the differential responses of firms from different emerging countries. To address this concern, we run a regression to show that uncertainty doesn't significantly affect social trust in our sample. The regression equation is as follows:

$$Trust_{c,t} = \alpha + \alpha_1 * Uncertainty_{c,t-1} + \Gamma * Macro_{c,t} + \Delta * Firm_{c,t} + v_c + v_t + v_{c,t} \tag{3}$$

where $Uncertainty_{c,t-1}$ is the 1-year lagged index of uncertainty measured by the standard deviation of daily stock return. $Firm_{c,t}$ is the country-year mean of $Firm_{i,t}$. $v_c$ and $v_t$

are country- and time- fixed effects, respectively. Other variables are the same as those in equation (1). We show the regression results in Appendix A2.6.

### 2.4.3 Extension

#### Debt and Equity

Our benchmark results concentrate on the impact of social trust on informal finance (trade credit) under aggregate uncertainty in EMEs. Existing literature shows that uncertainty also influences formal finance, such as debt and equity. Alfaro et al. (2018) and Gilchrist et al (2014) find that uncertainty significantly reduces debt issuance and financial frictions amplify these negative impacts. Jens (2017) uses U.S. gubernatorial elections as an index of variations in political uncertainty, and finds that firms postpone issuing debt and equity before elections. Does social trust also encourage firms in EMEs to issue more debt or equity when they are in face of uncertainty shocks? In this subsection, we investigate the role social trust plays in the transmission of uncertainty shocks to debt and equity issuance by estimating the following empirical specification:

$$Issuance_{j,i,c,t} = \theta_{0,j} + \theta_{1,j} * Trust_{c,t} * Uncertainty_{c,t-1} + \theta_{2,j} * Uncertainty_{c,t-1}$$

$$+\theta_{3,j} * Trust_{c,t} + \gamma_j * Firm_{i,t} + \delta_j * Macro_{c,t-1} + u_i + u_t + \epsilon_{j,i,c,t} \qquad (4)$$

where $j \in \{Debt, Equity\}$. $Issuance_{j,i,c,t}$ refers to debt or equity issuance for firm $i$, in country $c$, during period $t$. Recall that debt issuance corresponds to the growth rate of the sum of short- and long-term debt ($dlc$ and $dltt$, respectively), while equity issuance is equal to the growth rate of the sum of common/ordinary equity ($ceq$), deferred taxes ($txdb$) and minus retained earnings ($re$). Other variables are the same as those in equation (1).

To be consistent with our analyses of trade credit, we also divide the sample into two subsamples based on industry-level liquidity needs, and check whether the effects of social trust are heterogeneous. We are interested in the coefficients on the interaction term, $\theta_{1,j}$. The impact of social trust on formal financing channel is not clear. Hasan et al. (2017) find that social capital helps to lower at-issue bond spreads, and Lins et al. (2017) present firms with high levels of social capital raise more debt and had higher levels of stock return during the 2008-2009 financial crisis. Levine et al. (2018), however, argue that social trust doesn't exert a significant impact on debt or equity issuance during the banking crisis. In our analysis, if social trust affects firms' performance mainly through the trade credit channel, but not the formal financing channel, an insignificant or small $\beta_{1,j}$ is in favor of our argument.

Table 2.5

**Other Financing I**

| **Panel A: Debt** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.12 | 0.085 | 0.14 | 0.11 | 0.12 |
| | (0.12) | (0.12) | (0.16) | (0.12) | (0.16) |
| Uncertainty | -1.25 | -1.26 | -1.31 | -1.44 | -1.04 |
| | (3.48) | (3.17) | (4.37) | (3.12) | (4.26) |
| Trust | -0.14 | -0.30 | -0.052 | -0.34 | -0.039 |
| | (0.25) | (0.28) | (0.27) | (0.30) | (0.24) |
| Observations | 46,653 | 23,543 | 23,110 | 24,217 | 22,436 |
| Firms | 5,273 | 2,689 | 2,584 | 2,764 | 2,509 |
| $R^2$ | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Panel A in Table 5 show the results of the empirical specification: $Debt_{j,i,c,t} = \theta_{0,j} + \theta_{1,j} * Trust_{c,t} * Uncertainty_{c,t-1} + \theta_{2,j} * Uncertainty_{c,t-1} + \theta_{3,j} * Trust_{c,t} + \gamma_j * Firm_{i,t} + \delta_j * Macro_{c,t-1} + u_i + u_t + \epsilon_{j,i,c,t}$. $Debt_{j,i,c,t}$ refers to debt issuance for firm $i$, in country $c$, during period $t$. Recall that debt issuance corresponds to the growth rate of the sum of short- and long-term debt (*dlc* and *dltt* respectively). Other variables and the order of the regressions are same as those in Table 2.2. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Table 2.5

**Other Financing II**

| **Panel B: Equity** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | -0.088 | -0.061 | -0.11* | -0.10 | -0.076 |
| | (0.048) | (0.054) | (0.057) | (0.059) | (0.051) |
| Uncertainty | 2.25 | 1.83 | 2.65 | 2.46 | 2.05 |
| | (1.43) | (1.56) | (1.76) | (1.60) | (1.76) |
| Trust | -0.18 | -0.26 | -0.11 | -0.25 | -0.11 |
| | (0.16) | (0.16) | (0.17) | (0.18) | (0.17) |
| Observations | 46,725 | 23,574 | 23,151 | 24,253 | 22,472 |
| Firms | 5,264 | 2,677 | 2,587 | 2,752 | 2,512 |
| $R^2$ | 0.17 | 0.18 | 0.17 | 0.18 | 0.17 |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Panel B in Table 5 show the results of the empirical specification: $Equity_{j,i,c,t} = \theta_{0,j} + \theta_{1,j} * Trust_{c,t} * Uncertainty_{c,t-1} + \theta_{2,j} * Uncertainty_{c,t-1} + \theta_{3,j} * Trust_{c,t} + \gamma_j * Firm_{i,t} + \delta_j * Macro_{c,t} + u_i + u_t + \epsilon_{j,i,c,t}$. Equity issuance is equal to the growth rate of the sum of common/ordinary equity ($ceq$), deferred taxes ($txdb$) and minus retained earnings ($re$). Other variables and the order of the regressions are same as those in Table 2.2. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

We present the results in Table 2.5. Panel A shows the results concerning debt issuance, and Panel B equity issuance. The column order is also the same as that in Table 2.2. We can see no coefficients on the interaction term are significant even at the 10% level, whether using the full sample or the high-liquidity-needs group. The results suggest that social trust doesn't have a significant impact on firms' access to equity or debt when the aggregate economy suffers a positive uncertainty shock. From this perspective, social trust mainly affects firms' performance via the trade credit channel rather than by raising more debt or issuing more equity that depends more on formal legal arrangements.

**Profitability**

We have built up the relationship between social trust and firms' financing channel when the EMEs come across uncertainty shocks. Firms always adjust their formal and informal finance to keep their good performance or outcome. Thus, if social trust affects the impact of uncertainty on firms' finance in EMEs, it will alter the transmissions of uncertainty shocks to firms' performance. In this section, we use firms' profitability as the representative measure of firms' performance to test the interaction of uncertainty and social trust on firms' outcome. The empirical specification we use is as follows:

$$Profitability_{i,c,t} = \eta_0 + \eta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \eta_2 * Uncertainty_{c,t-1}$$

$$+\eta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t} \qquad (5)$$

$Profitability_{i,c,t}$ represents the profitability of firm $i$, in country $c$, during period $t$. Recall that we define firms' profitability as the ratio of earnings before interest and taxes (*ebit*) to total sales (*sale*) lagged for one period. Other independent variables are the same as those in equation (1) and (4).

We are still interested in the coefficient on the interaction of uncertainty and social trust, $\eta_1$, which captures the differential responses of firms' profitability to uncertainty shocks if firms come from countries with different levels of social trust. We predict that firms in countries with higher levels of social trust can make more profit than those firms in countries with lower levels of social trust via using more trade credit. A positive $\eta_1$ is in favor of our prediction. In line with the analyses on informal and formal financing, we assign firms into two subsamples based on the measures of liquidity needs. If social trust helps firms to keep their profits via receiving more trade credit from their suppliers in face of positive uncertainty shocks, firms in the high-liquidity-needs group benefit more from the higher level of social trust. A larger $\eta_1$ should enter the regression significantly when testing the interaction of social trust and uncertainty on firms' profitability of the high-liquidity needs group.

We present some preliminary visual results in Figure 2.4 and Figure 2.5, respectively. We construct two subsamples following Figure 2.2 and Figure 2.3, respectively. Figure 2.4(a) presents the relationship between aggregate uncertainty and the country-year mean of firms' profitability in the high-trust group, and Figure 2.4(b) presents the low-trust group. We can see that in the low-trust group, firms' profitability declines more as uncertainty increases, which is in line with our conjecture. Then we divide our sample into two groups based on industry-level liquidity needs. The observations whose liquidity needs are above the median are assigned into the high-liquidity-needs group, and others are in the low-liquidity-needs group. For each group, we construct two subsamples. One is the high-trust group whose social trust is in the upper quantile, whereas the other is the low-trust group whose trust is in the lower quantile. Figure 2.5(a) shows the relationship between aggregate uncertainty and firms' profitability for the group with high trust and high liquid needs, figure 2.5(b) for the group with low trust and high liquid needs, figure 2.5(c) for the group with low trust and low liquid needs, and figure 2.5(d) for the group with high trust and low liquid needs. We can see for the high-liquidity-needs group, firms in the high-trust countries suffer small drops in profitability.

The estimation results are shown in Table 2.6. The order of the regressions is still the same as in Table 2.2. We mainly have three findings. First, as with the regression using the full sample, the coefficient on the interaction of uncertainty and social trust is positive and significant at the 1% level. This implies that social trust can facilitate firms' profitability when the aggregate economy suffers an increase in uncertainty, as expected. Second, the coefficients on the interaction in the high-liquidity-needs group are positive and significant at the 1% level, no matter we use the ratio of inventory over total sales or the cash conversion cycles as the measure of industry-level liquidity needs. Third, the coefficients on the interaction term between the high and low groups are significantly different at the 10% level at least. Thus, firms in the high-liquidity-need group will benefit more as predicted.

To compute the size of the impact which social trust has on the transmission of uncertainty shocks to firms' profitability, we still consider firms in the high- and low-trust countries. With a one-standard-deviation increase in aggregate uncertainty, among firms in the high-trust country, their profitability experiences a 0.30-percentage-point ((32.5-17.6)*0.020) smaller contraction, compared to firms in the high-trust country. This magnitude (0.30)

Table 2.6
**Firms' Performance**

| **Panel A: EBIT** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.020*** | 0.028*** | 0.015* | 0.026*** | 0.017* |
| | (0.0065) | (0.0064) | (0.0083) | (0.0065) | (0.0085) |
| Uncertainty | -0.33 | -0.62*** | -0.090 | -0.52*** | -0.19 |
| | (0.22) | (0.14) | (0.35) | (0.14) | (0.34) |
| Trust | 0.033 | 0.0099 | 0.046* | 0.015 | 0.040 |
| | (0.024) | (0.025) | (0.027) | (0.025) | (0.027) |
| Observations | 46,560 | 23,559 | 23,001 | 24,242 | 22,318 |
| Firms | 5,244 | 2,681 | 2,563 | 2,759 | 2,485 |
| $R^2$ | 0.71 | 0.71 | 0.72 | 0.70 | 0.72 |
| F-Stat($\beta_H - \beta_L = 0$) | | 3.29* | | 1.55 | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $Profitability_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $Profitability_{i,c,t}$ refers to the ratio of earnings before interest and taxes over total assets by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the subsample of "High" liquidity need group and Column (iii) and (v) show the results on the results on the subsample of "Low" liquidity need group. Here the "High" group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Figure 2.4: **Social Trust, Uncertainty and Firms' Profitability**

Total Sample

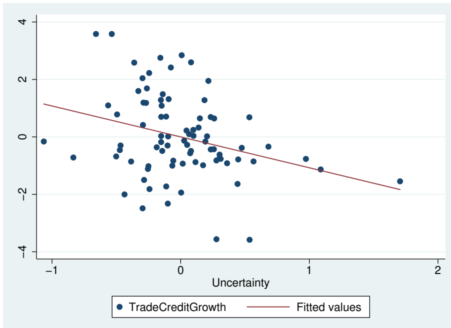



Figure 2.4(a)

Total Sample

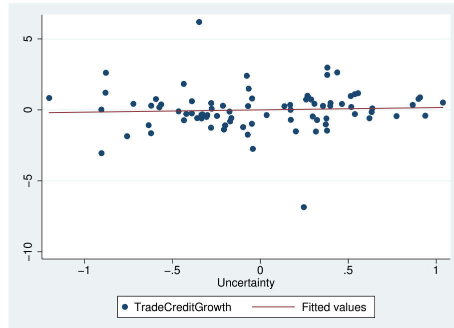



Figure 2.4(b)

This Figure shows the relationship between aggregate uncertainty and firms' profitability. We use the total sample and calculate the country-year mean of firm size, return on asset, book average and firms' profitability. We call the country-year observations whose social trust is in the upper quantile the high trust countries (Figure 2.4(b)) and the observations whose social trust is in the lower quantile the low trust countries (Figure 2.4(a)). The X-axis is the index of uncertainty and the Y-axis represents firms' profitability. We exclude firm size, return on asset, book leverage, macroeconomic vectors, country- and time- fixed effects from uncertainty and firms' profitability.

corresponds to 3.9% of the mean value of firms' profitability (7.60). If the firm is in the high-liquidity-need group, for example, those in the industry with a relatively high ratio of inventory over total sales, its profitability is 0.42 percentage point larger. This magnitude is larger than that of the regressions on the full sample. This finding is consistent with our prediction that firms which depend on liquid funds more benefit more from high social trust in face of positive uncertainty shocks.

Finally, to exclude the impact of other country-level characteristics, we add the interactions of uncertainty with the overall level of economic institution, the effectiveness of the legal system in enforcing contracts, the level of people's confidence in their government, and the degree to which the formal legal system protects creditors and shareholders in equation (5), respectively, to check the robustness of the impact of social trust on the transmissions of uncertainty shocks to firms' profitability. We find that the interactions of social trust and uncertainty keep their symbols and significance. We show these results in the Appendix A2.7.

Figure 2.5: **Social Trust, Uncertainty and Firms' Profitability**

The High-liquidity-needs Group

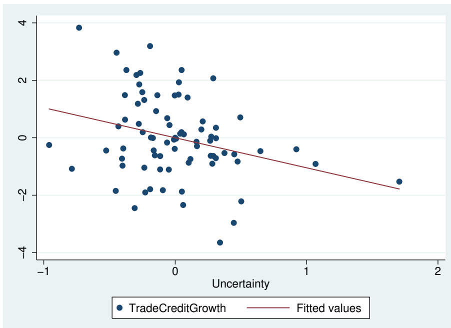



Figure 2.5(a)

The Low-liquidity-needs Group

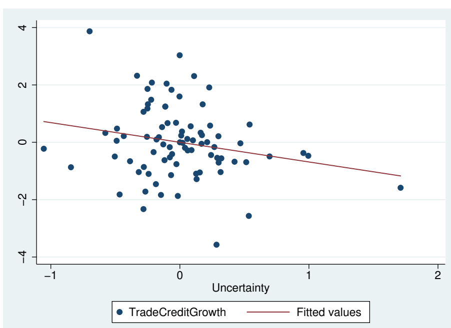



Figure 2.5(c)

**Low Social Trust Countries**

The High-liquidity-needs Group

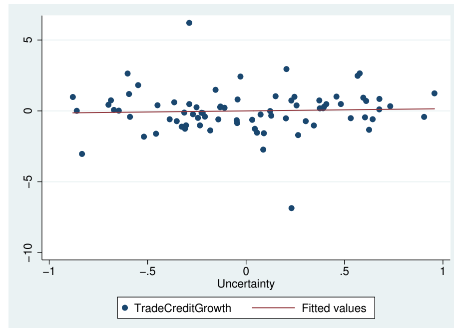



Figure 2.5(b)

The Low-liquidity-needs Group

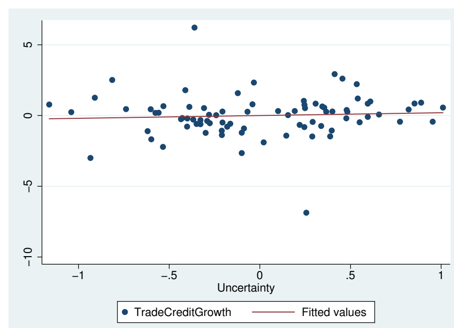



Figure 2.5(d)

**High Social Trust Countries**

This Figure shows the relationship between aggregate uncertainty and firms' profitability. We divide our sample into two subsamples based on industry-level liquidity needs. The observations whose liquidity needs are above the median are assigned into the high-liquidity-needs group and others are in the low-liquidity-needs group. For each group, we calculate the country-year mean of firm size, return on asset, book average and firms' profitability. We call the country-year observations whose social trust is in the upper quantile the high trust countries (Figure 2.5(b) and 2.5(d)) and the observations whose social trust is in the lower quantile the low trust countries (Figure 2.5(a) and 2.5(c)). The X-axis is the index of uncertainty and the Y-axis represents firms' profitability. We exclude firm size, return on asset, book leverage, macroeconomic vectors, country- and time- fixed effects from uncertainty and firms' profitability.

## 2.5 Conclusion

This paper argues that social trust can help firms to keep their good performance via receiving more trade credit when the aggregate economy suffers a positive uncertainty shock in emerging countries. Our analyses suggest that i) social trust can make firms easier to get access to trade credit during periods of uncertainty; ii) firms' profitability suffers smaller drops in face of uncertainty shocks if they are in countries with higher levels of social trust, and iii) firms which depend on liquid funds more will benefit more from the greater social trust. Our findings are robust, if we exclude the impact of other country-level characteristics, with the overall level of economic institution, the effectiveness of the legal system in enforcing contracts, the level of people's confidence in their government and the degree to which the formal legal system protects creditors and shareholders included respectively. Also, our results still hold, if we use a different measure of aggregate uncertainty.

## 2.6 Appendix

Appendix A2.1

**Clustered at Country and Year**

| | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.24*** | 0.39*** | 0.12** | 0.33*** | 0.17*** |
| | (0.073) | (0.097) | (0.062) | (0.010) | (0.060) |
| Uncertainty | -6.67*** | -9.50*** | -4.50** | -8.32*** | -5.38*** |
| | (2.07) | (2.97) | (1.72) | (2.93) | (1.71) |
| Trust | -0.16 | -0.036 | -0.32** | 0.042 | -0.37*** |
| | (0.12) | (0.16) | (0.13) | (0.16) | (0.12) |
| Fixed Effect | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,782 | 24,133 | 23,649 | 24,834 | 22,948 |
| Firms | 5,323 | 2,714 | 2,609 | 2,790 | 2,533 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 10.26*** | | 3.20* | |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$. where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time-fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the high-liquidity-needs group, and Column (iii) and (v) show the results on the results on the low-liquidity-needs group. Here, the high group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.2

**Interactions of Uncertainty and Macroeconomic Variables**

| | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.23*** | 0.37*** | 0.11*** | 0.32*** | 0.15** |
| | (0.063) | (0.10) | (0.049) | (0.093) | (0.052) |
| Uncertainty | -6.92*** | -9.42** | -4.95*** | -8.79*** | -5.24*** |
| | (2.19) | (3.51) | (1.73) | (3.10) | (1.84) |
| Trust | -0.11 | 0.081 | -0.31* | 0.15 | -0.36** |
| | (0.16) | (0.20) | (0.17) | (0.20) | (0.16) |
| Fixed Effect | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,782 | 24,133 | 23,649 | 24,834 | 22,948 |
| Firms | 5,323 | 2,714 | 2,609 | 2,790 | 2,533 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 7.30*** | | 4.85** | |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \beta_4 * Macro_{c,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the high-liquidity-needs group, and Column (iii) and (v) show the results on the results on the low-liquidity-needs group. Here, the high group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.3

**Interactions of Uncertainty and Firm Variables**

| | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.20*** | 0.38*** | 0.058 | 0.31*** | 0.11** |
| | (0.059) | (0.083) | (0.056) | (0.081) | (0.053) |
| Uncertainty | -10.11*** | -10.15** | -10.55*** | -10.31** | -10.19*** |
| | (3.15) | (4.76) | (2.19) | (4.48) | (2.54) |
| Trust | -0.15 | -0.027 | -0.30* | 0.061 | -0.36** |
| | (0.16) | (0.20) | (0.15) | (0.21) | (0.15) |
| Fixed Effect | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,782 | 24,133 | 23,649 | 24,834 | 22,948 |
| Firms | 5,323 | 2,714 | 2,609 | 2,790 | 2,533 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 17.51*** | | 8.63*** | |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \beta_4 * Firm_{i,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and (iv) show the results on the high-liquidity-needs group, and Column (iii) and (v) show the results on the results on the low-liquidity-needs group. Here, the high group means that the ratio of inventories over sales or the cash conversion cycle is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.4

**New Measure of Liquidity Needs**

| | Full | Liquid Needs | |
|---|---|---|---|
| | | High | Low |
| | (i) | (ii) | (iii) |
| Uncertainty*Trust | 0.24*** | 0.34*** | 0.14 |
| | (0.065) | (0.060) | (0.091) |
| Uncertainty | -6.67*** | -10.28*** | -3.12 |
| | (2.14) | (2.13) | (2.56) |
| Trust | -0.16 | -0.32 | 0.024 |
| | (0.14) | (0.15) | (0.19) |
| Fixed Effect | | | |
| Time | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes |
| Observations | 47,782 | 23,971 | 23,811 |
| Firms | 5,323 | 2,681 | 2,642 |
| $R^2$ | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 5.57** | |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the regression results of the empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $tcgr_{i,c,t}$ refers to the growth rate of account payable by firm $i$, in country $c$, during period $t$; $Trust_{c,t}$ represents the measure of social trust in emerging country $c$ over the period $t$; and $Uncertainty_{c,t-1}$ is the index of uncertainty measured by the standard deviation of daily stock market return for country $c$ in the period $t-1$. $Firm_{i,t}$ denotes a set of time-varying firm characteristics such as firms' size in the corresponding period. $Macro_{c,t}$ is a vector of time-variant country-level variables (e.g. GDP per Capita, Financial Development and Capital Account Openness). $u_i$ and $u_t$ are firm- and time- fixed effects respectively. Column (i) presents the results on the full sample. Column (ii) and Column (iii) show the results on the results on the high- and low-liquidity-needs group, respectively. Here, the high group means that the ratio of short debt to total sales is above the median. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.5

**Micro Uncertainty and Additional Controls I**

| **Panel A: Institution** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.39*** | 0.57*** | 0.27*** | 0.65*** | 0.19** |
| | (0.095) | (0.15) | (0.076) | (0.15) | (0.084) |
| Uncertainty | -8.53*** | -12.91*** | -5.51* | -15.25*** | -3.43 |
| | (3.08) | (4.25) | (2.74) | (3.86) | (3.38) |
| Trust | -0.43** | -0.37 | -0.57*** | -0.38 | -0.57*** |
| | (0.18) | (0.25) | (0.16) | (0.26) | (0.14) |
| Uncertainty*Institution | 0.20*** | 0.21* | 0.17* | 0.22* | 0.13 |
| | (0.064) | (0.10) | (0.087) | (0.11) | (0.094) |
| Institution | -0.52** | -0.75* | -0.39* | -0.56 | -0.58** |
| | (0.24) | (0.39) | (0.19) | (0.34) | (0.21) |
| Observations | 31,994 | 16,110 | 15,884 | 16,551 | 15,443 |
| Firms | 4,071 | 2,078 | 1,993 | 2,131 | 1,940 |
| $R^2$ | 0.12 | 0.12 | 0.13 | 0.12 | 0.13 |
| F-Stat($\beta_H - \beta_L = 0$) | | 6.39** | | 12.83*** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table uses the following empirical empirical specification: $tcgr_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \beta_4 * CC_{c,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $CC_{c,t} \in \{Institution_{c,t}, Law_{c,t}, GovTrust_{c,t}, CR_c, AntiSelf_c\}$. $Institution_{c,t}$ is the overall level of country $i$'s economic institution in period $t$. $Law_{c,t}$ measures the effectiveness of the legal system in enforcing contracts in country $c$ during year $t$. $GovTrust_{c,t}$ represent people's confidence in their government in year $t$ for country $c$. $CR_c$ denotes the the strength of the legal rights of creditors and $AntiSelf_c$ reflects the degree to which the legal systems protects small investors from self-dealing by corporate insiders. Other variables are same with those in Table 4. The column order of the regressions is same with those in Table 4. Column (i) provides the results on the full sample, column (ii) and (iv) provide the results of the high-liquidity-needs group, and column( iii) and (v) show the results of the low-liquidity-needs group. In panel A, we include the interaction of uncertainty and the overall level of economic institution to exclude the impact of institutional quality. Panel B exclude the impact of the effectiveness of the legal systems, Panel C the impact of people's confidence in their government, Panel D the impact of creditor right protections and Panel E the impact of the protection on shareholders. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.5 (Continue)

**Micro Uncertainty and Additional Controls II**

| **Panel B: Law** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.28*** | 0.35*** | 0.23*** | 0.40*** | 0.19** |
| | (0.065) | (0.10) | (0.060) | (0.12) | (0.065) |
| Uncertainty | -5.03** | -6.26* | -3.83** | -8.72*** | -2.10 |
| | (2.10) | (3.13) | (1.79) | (2.86) | (2.23) |
| Trust | -0.33** | -0.27 | -0.40** | 0.17 | -0.49*** |
| | (0.14) | (0.16) | (0.16) | (0.17) | (0.16) |
| Uncertainty*Law | 0.0023 | 0.00050 | 0.0025 | -0.0068 | 0.0087 |
| | (0.017) | (0.025) | (0.014) | (0.029) | (0.012) |
| Law | 0.062 | 0.096 | 0.038 | 0.073 | 0.056 |
| | (0.080) | (0.11) | (0.068) | (0.11) | (0.074) |
| Observations | 35,798 | 17,942 | 17,856 | 18,717 | 17,081 |
| Firms | 4,392 | 2,238 | 2,154 | 2,333 | 2059 |
| $R^2$ | 0.12 | 0.12 | 0.13 | 0.12 | 0.13 |
| F-Stat($\beta_H - \beta_L = 0$) | | 1.62 | | 2.65 | |
| **Panel C: Government Trust** | | | | | |
| Uncertainty*Trust | 0.29*** | 0.40** | 0.20*** | 0.45*** | 0.16** |
| | (0.083) | (0.14) | (0.062) | (0.15) | (0.062) |
| Uncertainty | -4.97* | -6.53 | -3.93 | -8.11* | -2.97 |
| | (2.82) | (4.32) | (2.36) | (4.27) | (2.54) |
| Trust | -0.13 | -0.045 | -0.23 | -0.085 | -0.20 |
| | (0.24) | (0.37) | (0.180) | (0.36) | (0.20) |
| Uncertainty*GovTrust | -0.033 | 0.039 | -0.082 | 0.039 | -0.10 |
| | (0.063) | (0.10) | (0.067) | (0.097) | (0.065) |
| GovTrust | -0.0097 | 0.034 | -0.066 | 0.15 | -0.21 |
| | (0.18) | (0.21) | (0.021) | (0.19) | (0.22) |
| Observations | 38,966 | 19,684 | 19,282 | 20,266 | 18,700 |
| Firms | 4,390 | 2,257 | 2,133 | 2,324 | 2,066 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.12 |
| F-Stat($\beta_H - \beta_L = 0$) | | 2.93* | | 4.60** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix A2.5 (Continue)

**Micro Uncertainty and Additional Controls III**

| **Panel D: creditor rights** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.29*** | 0.42*** | 0.20*** | 0.47*** | 0.15** |
| | (0.074) | (0.13) | (0.065) | (0.14) | (0.062) |
| Uncertainty | -4.97** | -7.27* | -3.52* | -8.96** | -2.35 |
| | (2.28) | (3.69) | (1.75) | (3.63) | (2.02) |
| Trust | -0.28* | -0.25 | -0.35** | -0.19 | -0.40** |
| | (0.14) | (0.14) | (0.15) | (0.16) | (0.14) |
| Uncertainty*CR | 0.25 | 0.0079 | 0.28 | 0.14 | 0.20 |
| | (0.83) | (1.14) | (0.84) | (1.12) | (0.92) |
| Observations | 39,738 | 19,885 | 19,853 | 20,706 | 19,032 |
| Firms | 4,441 | 2,260 | 2,181 | 2,355 | 2,086 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.12 |
| F-stat($\beta_H - \beta_L = 0$) | | 2.93* | | 4.70** | |
| **Panel E: Anti-Self dealing** | | | | | |
| Uncertainty*Trust | 0.30*** | 0.41*** | 0.23*** | 0.46*** | 0.18*** |
| | (0.079) | (0.14) | (0.056) | (0.14) | (0.055) |
| Uncertainty | -5.45* | -6.88 | -4.75** | -8.20* | -3.87* |
| | (2.79) | (4.38) | (1.85) | (4.33) | (2.00) |
| Trust | -0.28* | -0.24 | -0.37** | -0.18 | -0.42*** |
| | (0.13) | (0.14) | (0.14) | (0.15) | (0.14) |
| Uncertainty*AntiSelf | -2.31 | 2.59 | -5.71 | 4.82 | -7.83* |
| | (5.86) | (8.47) | (4.20) | (8.80) | (4.07) |
| Observations | 39,738 | 19,885 | 19,853 | 20,706 | 19,032 |
| Firms | 4,441 | 2,260 | 2,181 | 2,355 | 2,086 |
| $R^2$ | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |
| F-stat($\beta_H - \beta_L = 0$) | | 2.47 | | 4.39** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix A2.6

**The Relationship between Social Trust and Aggregate Uncertainty**

| | (i) | (ii) | (iii) |
|---|---|---|---|
| Uncertainty | -0.089 | -0.15 | -0.089 |
| | (0.32) | (0.39) | (0.398) |
| Size | | | -0.37 |
| | | | (0.30) |
| Return on Assets | | | -12.19 |
| | | | (12.53) |
| Book Leverage | | | 2.21 |
| | | | (4.41) |
| GDPper | | -1.64 | -1.52 |
| | | (1.39) | (1.50) |
| Financial Development | | -0.074* | -0.084** |
| | | (0.040) | (0.040) |
| Stock Market | | 0.056* | 0.055* |
| | | (0.030) | (0.030) |
| Capital Openness | | -0.34 | -0.47 |
| | | (1.67) | (1.72) |
| Liquid | | 0.0036 | 0.0044 |
| | | (0.018) | (0.019) |
| Fixed Effect | | | |
| Time | Yes | Yes | Yes |
| Country | Yes | Yes | Yes |
| Observations | 330 | 330 | 330 |
| Amount of Economies | 26 | 26 | 26 |
| $R^2$ | 0.83 | 0.84 | 0.84 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; and $^{*}p < 0.1$. The estimation is based on the regression specification: $Trust_{c,t} = \eta_0 + \eta_1 * Uncertainty_{c,t-1} + \Delta * Macro_{c,t} + u_t + \epsilon_{c,t}$, where $Uncertainty_{c,t}$ and $Trust_{c,t}$ refer to aggregate uncertainty in country $c$ and the social trust in country $c$ during period $t$ . $Firm_{c,t}$ is the country-year mean of $Firm_{i,t}$. $Macro_{c,t}$ is the vector of macroeconomic controls. Standard errors are clustered at the country level.

Appendix A2.7

**Firms' Performance and Other Factors I**

| **Panel A: Institution** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.021*** | 0.037*** | 0.0088 | 0.031*** | 0.013 |
| | (0.0068) | (0.0083) | (0.0083) | (0.0077) | (0.0086) |
| Uncertainty | -0.36 | -1.01*** | 0.20 | -0.81*** | 0.028 |
| | (0.24) | (0.30) | (0.29) | (0.25) | (0.31) |
| Trust | 0.050** | 0.044 | 0.047** | 0.045 | 0.043 |
| | (0.020) | (0.029) | (0.022) | (0.031) | (0.024) |
| Uncertainty*Institution | 1.04 | 0.87 | 1.08 | 0.99 | 1.03 |
| | (0.69) | (0.77) | (0.85) | (0.62) | (0.99) |
| Institution | -2.75 | -2.57 | -2.89 | -1.77 | -3.58 |
| | (3.06) | (2.57) | (4.30) | (2.85) | (4.19) |
| Observations | 33,893 | 17,014 | 16,879 | 17,483 | 16,410 |
| Firms | 4,574 | 2,320 | 2,254 | 2,379 | 2,195 |
| $R^2$ | 0.73 | 0.72 | 0.74 | 0.72 | 0.74 |
| F-Stat($\beta_H - \beta_L = 0$) | | 7.86*** | | 4.18** | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the regression results of the empirical specification: $Profitability_{i,c,t} = \beta_0 + \beta_1 * Trust_{c,t} * Uncertainty_{c,t-1} + \beta_2 * Uncertainty_{c,t-1} + \beta_3 * Trust_{c,t} + \beta_4 * CC_{c,t} * Uncertainty_{c,t-1} + \gamma * Firm_{i,t} + \delta * Macro_{c,t} + u_i + u_t + \epsilon_{i,c,t}$, where $CC_{c,t} \in \{Institution_{c,t}, Law_{c,t}, GovTrust_{c,t}, CR_c, AntiSelf_c\}$. $Institution_{c,t}$ is the overall level of country $i$'s economic institution in period $t$. $Law_{c,t}$ measures the effectiveness of the legal system in enforcing contracts in country $c$ during year $t$. $GovTrust_{c,t}$ represent people's confidence in their government in year $t$ for country $c$. $CR_c$ denotes the the strength of the legal rights of creditors and $AntiSelf_c$ reflects the degree to which the legal systems protects small investors from self-dealing by corporate insiders. Other variables are same with those in Table 6. The column order of the regressions is same with those in Table 6. Column (i) provides the results on the full sample, column (ii) and (iv) provide the results of the high-liquidity-needs group, and column( iii) and (v) show the results of the low-liquidity-needs group. In panel A, we include the interaction of uncertainty and the overall level of economic institution to exclude the impact of institutional quality. Panel B exclude the impact of the effectiveness of the legal systems, Panel C the impact of people's confidence in their government, Panel D the impact of creditor right protections and Panel E the impact of the protection on shareholders. Heteroscedasticity robust standard errors clustered at the country level are reported in parentheses.

Appendix A2.7 (Continue)

**Firms' Performance and Other Factors II**

| **Panel B: Law** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.020*** | 0.032*** | 0.012 | 0.030*** | 0.013 |
| | (0.0065) | (0.0075) | (0.0080) | (0.0070) | (0.0086) |
| Uncertainty | -0.30 | -0.56*** | -0.11 | -0.49*** | -0.15 |
| | (0.24) | (0.15) | (0.36) | (0.16) | (0.37) |
| Trust | 0.017 | -0.0028 | 0.031 | 0.0038 | 0.025 |
| | (0.025) | (0.023) | (0.030) | (0.023) | (0.031) |
| Uncertainty*Law | 0-0.041 | 0.14 | -0.18 | 0.015 | -0.082 |
| | (0.096) | (0.094) | (0.12) | (0.085) | (0.14) |
| Law | 1.04 | 1.47 | 0.42 | 1.49 | 0.39 |
| | (0.81) | (0.094) | (1.09) | (0.83) | (1.05) |
| Observations | 42,344 | 21,174 | 21,170 | 22,128 | 20,216 |
| Firms | 5,165 | 2,695 | 2,560 | 2,723 | 2,442 |
| $R^2$ | 0.73 | 0.72 | 0.74 | 0.72 | 0.74 |
| F-Stat($\beta_H - \beta_L = 0$) | | 4.82** | | 3.49* | |
| **Panel C: Government Trust** | | | | | |
| Uncertainty*Trust | 0.020*** | 0.030*** | 0.013 | 0.028*** | 0.014* |
| | (0.0065) | (0.0073) | (0.0079) | (0.0072) | (0.0079) |
| Uncertainty | -0.28 | -0.51*** | -0.097 | -0.42** | -0.18 |
| | (0.21) | (0.16) | (0.33) | (0.16) | (0.32) |
| Trust | 0.044 | 0.011 | 0.063 | 0.016 | 0.058 |
| | (0.031) | (0.035) | (0.037) | (0.036) | (0.039) |
| Uncertainty*GovTrust | -0.0053 | -0.0063 | -0.0087 | -0.0032 | -0.0072 |
| | (0.0045) | (0.0057) | (0.0060) | (0.0048) | (0.0063) |
| GovTrust | 0.018 | 0.052** | -0.013 | 0.052** | -0.018 |
| | (0.017) | (0.019) | (0.021) | (0.021) | (0.024) |
| Observations | 45,230 | 22,853 | 22,377 | 23,551 | 21,679 |
| Firms | 5,156 | 2,630 | 2,526 | 2,713 | 2,443 |
| $R^2$ | 0.71 | 0.71 | 0.72 | 0.70 | 0.72 |
| F-Stat($\beta_H - \beta_L = 0$) | | 5.08** | | 2.99* | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Appendix A2.7 (Continue)

**Firms' Performance and Other Factors III**

| **Panel D: creditor rights** | Full | Liquid Needs | | Cycles | |
|---|---|---|---|---|---|
| | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Uncertainty*Trust | 0.021*** | 0.028*** | 0.015* | 0.026*** | 0.017** |
| | (0.0064) | (0.0067) | (0.0080) | (0.0067) | (0.0080) |
| Uncertainty | -0.34 | -0.64*** | -0.10 | -0.53*** | -0.20 |
| | (0.22) | (0.15) | (0.32) | (0.15) | (0.32) |
| Trust | 0.031 | 0.0089 | 0.043 | 0.015 | 0.036 |
| | (0.024) | (0.024) | (0.026) | (0.026) | (0.026) |
| Uncertainty*CR | -0.037 | 0.039 | -0.087 | 0.055 | -0.11 |
| | (0.082) | (0.089) | (0.10) | (0.075) | (0.11) |
| Observations | 46,241 | 23,366 | 22,875 | 24,043 | 22,198 |
| Firms | 5,176 | 2,639 | 2,537 | 2,716 | 2,460 |
| $R^2$ | 0.71 | 0.71 | 0.72 | 0.71 | 0.72 |
| F-stat($\beta_H - \beta_L = 0$) | | 3.81* | | 2.07 | |
| **Panel E: Anti-Self dealing** | | | | | |
| Uncertainty*Trust | 0.020*** | 0.027*** | 0.014* | 0.025*** | 0.017** |
| | (0.0053) | (0.0059) | (0.0074) | (0.0062) | (0.0074) |
| Uncertainty | 0.040 | -0.27 | 0.29 | -0.21 | 0.24 |
| | (0.21) | (0.24) | (0.32) | (0.21) | (0.31) |
| Trust | 0.029 | 0.0054 | 0.042 | 0.011 | 0.036 |
| | (0.024) | (0.024) | (0.026) | (0.025) | (0.026) |
| Uncertainty*AntiSelf | -0.70** | -0.66** | -0.72* | -0.58** | -0.81* |
| | (0.28) | (0.26) | (0.41) | (0.26) | (0.40) |
| Observations | 46,278 | 23,446 | 22,832 | 24,135 | 22,143 |
| Firms | 5,165 | 2,649 | 2,516 | 2,729 | 2,436 |
| $R^2$ | 0.71 | 0.71 | 0.72 | 0.70 | 0.72 |
| F-stat($\beta_H - \beta_L = 0$) | | 2.61 | | 1.30 | |
| Firm Controls | Yes | Yes | Yes | Yes | Yes |
| Macro Controls | Yes | Yes | Yes | Yes | Yes |
| Time&Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

# Chapter 3

# Social Connections and the Transmissions of Monetary Contraction Shocks

## 3.1 Introduction

Corporate senior managers and board members have wide-ranging social networks, built up through alumni associations, previous employment, and memberships in clubs. Since Coleman's (1988) work on the relationship between social interactions and economic behaviors, there has been a growing body of literature that considers the impact of social connections on areas of corporate finance. There are two primary channels through which social connections can affect corporate financial decision making: they lower the cost of gathering business-relevant information and they enhance trust between parties. Both of these can reduce the frictions agents face on the market, which in turn affects the transmissions of macroeconomic shocks[1]. However, to date, there has been relatively little empirical evidence documenting the link between social connections and macroeconomic shocks.

This paper investigates how the existence of social connections between executives of downstream and upstream firm pairs affects their transactions when they face monetary contraction shocks. We measure the extent to which a pair is socially connected by whether the supplier's senior executives have in the past attended the same university or worked at the same firm for an overlapping period as senior executives from the customer firm. As this definition makes clear, like Ishii and Xuan (2014) and Dasgupta et al. (2018), we work with cross-firm connections. In this paper, we examine the effects of social connections in the context of relatively large between-firm sales[2] because these sales have a sizable impact on firm performance, and thus usually need a relatively complex decision-making process. Sales between firms decrease in response to a monetary recession shock due to worse liquid conditions, however, this is affected by social connections.

We find that sales between socially connected pairs account for a greater fraction of suppliers' total sales than those of socially unconnected pairs during monetary contractions. That is, when the economy suffers a monetary contraction shock, suppliers sell more products to those customers to whose executives their executives have at least one education or employment tie. When the index by which we capture monetary shocks increases by 1 standard deviation, the ratio of the pair-level sales to suppliers' total sales for the socially connected pairs will be 4.3% larger than the same ratio for unconnected pairs. Taking pairs whose sales to suppliers' total sales ratio is at the median level (0.15), this amounts to a

[1]For example, Bernanke et al. (1999) see information monitoring costs between lenders and borrowers as a financial friction. The higher the cost, the more severe the friction

[2]In our sample, over 99% of the pairs' sales exceed 1% of the total sales of the corresponding supplier and almost 95% sales exceed 4%.

0.65 percentage point increase. For suppliers whose sales are around the median ($311m), this equals about $2m.

One explanation for this result is that during monetary recession periods, it becomes more costly for firms to borrow from financial intermediaries like commercial banks. The financial literature shows that firms will provide more trade credit during periods of tight domestic credit[3]. Transactions between upstream and downstream firms will depend on trade credit to a greater extent when the economy faces a monetary shock. Suppliers sign trade credit contracts with the customers and such contracts are typically implemented in the near future. However, there is an asymmetric information problem. Suppliers cannot fully confirm customers' ability to repay the debt. Thus, there is a hold-up problem. Social connections between executives can help mitigate this problem, as they can lower the cost of gathering information about the other party, and enhance the trust between them. In line with this, Wu et al. (2014) find that suppliers in higher-social-trust regions extend more trade credit to the private firms in China. Also related, Levine et al. (2018) argue that highly-liquidity-dependent firms in high-trust countries get more trade credit and social trust can ease the consequence of banking crises.

We cannot directly test whether this explanation, information-gathering and trust operating through trade credit, drives our result, as we do not observe within-pair trade credit. Indirectly, however, we can examine the plausibility of this channel by investigating its implications. First, if during monetary contractions, suppliers extend more trade credit to customers to whom they are socially connected, then sales between them should increase when the customers' account payable increases. That is, the pairs' sales should be more sensitive to customers' changes in the cash flow of account payable. Second, suppliers should provide more trade credit in total if their main customers are more financially constrained or have higher levels of trade credit dependence. To implement this, we divide our sample by customer industry-level external financial dependence or liquidity needs, and check whether suppliers which have more socially connected customers in our data will extend more trade credit in response to a monetary shock. Third, if one reason social connections affect the provision of trade credit and ultimately sales between firms is trust, we should expect the trust of personal connections to be particularly important when background trust is high. To investigate this, we divide our sample by state-level social trust and reestimate the main effects.

[3] Eg. Lin and Ye 2017; Petersen and Rajan 1997; Fisman and Love 2003; Fisman and Raturi 2004; Mateut, Bougheas, and Mizen 2006; Nilsen 2002.

In our empirical analyses, we find that during periods of monetary contractions, sales of socially connected pairs are more sensitive to the use of trade credit. If the ratio of changes in customer firms' account payable over their current liabilities increases by 1 percentage points, sales between the pair will on average increase by 0.32%, about 10.3% of the mean level (3.1%) of the interaction of monetary recessions and social connections on sales. This result confirms the first implication of the trade credit explanation we described above. For the second implication, in the sample of high external financial dependence, our finding is as follows. When the index of monetary policy increases by 1 standard deviation, cash flow of account receivable (scaled by sales) of socially connected suppliers on average increases 0.63 percentage point more than the cash flow of unconnected suppliers. However, in the low external financial dependence sample, this impact is not significant. A similar pattern emerges when we divide the sample not by external financial dependence but by customer liquidity needs. This is consistent with the trade credit channel. Finally, for the third implication, when we divide our sample by state-level social trust, we find that the magnitude of our main effect is larger if suppliers are located in states with relatively high social trust.

## 3.2 Literature Review

Our paper contributes to the literature studying the impact of social connections on firm decision-making and performance. This literature studies both within-firm connections and cross-firm connections, which our paper contributing to the latter. Ishii and Xuan (2014) identify social connections by one's education and job network. They find a negative impact of social ties between acquirers and targets on merger performance. This finding supports the hypothesis that social ties between an acquirer and a target lead to a weaker critical analysis, lowering standards or missed opportunities. Using the educational and job social ties but constructing a different measure of cross-firm connections, Dasgupta et al. (2018) show that prior social connections between downstream and upstream firms can mitigate the hold-up problems and foster R&D. Xue et al. (2018) use a sample of U.S. firms and their IT suppliers and find that the interfirm managerial social ties increase the diversity of firms' IT component diversity. Our paper also uses the education and job network to identify the social connections across firms like Dasgupta et al. (2018). However, we focus on the effects of social connections on the transmission of monetary shocks.

In our analyses, we argue that one reason social connections affect sales is that they affect trust. This relates our paper to the literature studying the impact of social trust/capital.

Knack and Keefer (1997) provide strong evidence that trust and civil cooperation significantly affect aggregate economic activities. Levine et al. (2018) use the same measure of social trust, but investigate the impact at the firm level. They find that firms with higher levels of liquidity dependence suffer smaller declines in employment and profit in the presence of banking crisis if they are located in the countries with higher levels of social trust, because they can get more trade credit. Lins et al. (2017) use a different measure, corporate social responsibility intensity, and find that firms with high social capital had a higher stock return during the 2008-2009 financial crisis. In all these papers, it is not clear where social trust comes from. In our work, we argue that personal social connections may be an origin of trust, as proposed by sociologists. For example, McPherson et al. (2001) argue that homophily in social networks limits people's social worlds in a way that has powerful implications for the attitudes they form. Glanville et al. (2013) use panel data to show that social ties improve the sense of trust.

Other than enhancing trust, social connections facilitate the transfer of information. Cohen et al. (2008) identify information transfer in the security market via educational networks between mutual fund managers and corporate board members. The social network between analysts and firms also helps sell-side analysts collect superior information about firms (Cohen et al. 2010). The information-sharing function can help to mitigate the hold-up problem due to asymmetric information when the suppliers and customers sign a trade credit contract. This links our work to studies about the relationship between information advantage and trade credit. Petersen and Rajan (1997) and Biais and Gollier (1997) show that suppliers which have a comparative advantage in obtaining information about buyers offer more trade credit to them.

Finally, our paper test the impact of monetary policy shocks on the pair-level sales and trade credit, which adds to the literature related to the transmission of monetary policy. This literature is too large to fully review here. To point to some related work, Mateut et al. (2006) theoretically show that the ratio of bank lending relative to trade credit decreases when the economy suffers a monetary tightness shock and confirm this finding through an empirical analysis using UK manufacturing firms. Choi and Kim (2005) use a firm-level panel and find that both accounts receivable and payable increase during periods of monetary tightness. The results in our paper are consistent with these results.

## 3.3 Data

The main pair-level firm data used in our empirical analyses is extracted from the Compustat Segment files. Suppliers are required to disclose the identities of customers account for more than 10% of their sales. The dataset contains detailed information about suppliers' main customers and the corresponding sales between them. We exclude generic customers whose name contains "vendor", "major", "foreign", "sales", "reported", "gov" and "customers". We also exclude firm types other than companies. Finally, we also exclude financial services and utilities using SIC identifiers from 4900 to 4999 and from 6000 to 6999. To mitigate the effects of outliers and possible measurement errors, we trim our sample by 1%. Our sample starts from 2000 because the social connection information of most companies is incomplete before 2000. In the benchmark analyses, our sample extends to 2016. In the robustness check, we restrict our sample to 2007 to sidestep any concerns associated with the 2008 financial crisis and the zero-lower-bound period.

We obtain suppliers' and customers' financial information from Compustat. The dataset contains details on investment, capital structure, cash flow and balance sheet items. We match suppliers' financial information with the pair-level data (Compustat Segment) by the cik and cusip identifiers. However, as with customers, Compustat Segment doesn't provide any identifier which we can use to match customers' financial information. Customers are listed by suppliers by the name of the firm as opposed to a unique identifier that would allow us to obtain their financial information in the data. As a result, we match these names to firm names in Compustat with the following procedure. First, we pre-process firm names, removing common strings such as "corp", "Inc" etc. Second, we check for direct name matches. For company names that remain without a direct match, we follow the natural language processing literature and find candidate matches by transforming firm names computing distance measures between them. We find that the Jaccard-distance on sets of 3-grams of firm names works well. We select the match with the greatest similarity (shortest distance). Finally, we manually check best matches to ensure they refer to the same company.

We divide suppliers and customers at the two-digit levels according to Standard Industrial Classification (SIC). We construct industry-level data based on the Compustat Capital IQ-North America-Fundamental Annual, which compiles balance sheets and income statements for US-listed firms.

Table 3.1
**Statistical Descriptions**

| | Mean | Min | Max | Median | S.D. |
|---|---|---|---|---|---|
| **Dependent Variable** | | | | | |
| Pair-Sale/Supplier-Sale | 0.20 | 0.0078 | 1 | 0.15 | 0.16 |
| Suppliers' Account Receivable (changes)/Total Assets*100 | 0.95 | -32.32 | 35.99 | 0.75 | 6.40 |
| **Independent Variables** | | | | | |
| social connection dummy | 0.34 | 0 | 1 | 0 | 0.47 |
| weak social connection dummy | 0.47 | 0 | 1 | 0 | 0.50 |
| monetary contraction index | 0 | -2.42 | 1.70 | 0 | 1 |
| **Other controls** | | | | | |
| log(Suppliers' asset) | 5.88 | -5.12 | 10.62 | 5.85 | 1.85 |
| Suppliers' Profitability | 0.054 | -3.32 | 1.39 | 0.10 | 0.23 |
| Suppliers' Asset Tangibility | 0.22 | 0 | 0.98 | 0.14 | 0.22 |
| log(Customers' asset) | 10.21 | 3.41 | 13.86 | 10.37 | 1.60 |
| Distance | 1479.89 | 0 | 12756.91 | 711.69 | 2279.49 |
| Relationship | 0.28 | 0 | 21 | 0 | 1.20 |

### 3.3.1 Social Connections

To capture social connections, we use BoardEx, which has extensive data on the boards of publicly listed and notable private companies in all regions of the world, including their education, prior employment and current role. We link our data to BoardEx using the cusip and cik firm identifiers. As we want to study the extent to which social connections moderate the impact of monetary policy, we restrict the set of executives we examine to those that have important roles. Specifically, we restrict our attention to executives whose role description contain any of the following words: ceo, cfo, coo, chairman, president, executive vp, general manager, md, manager, partner, president, senior vp, vice president, owner, leader.

Then we construct our measures of social connections as follows. For each supplier-customer pair at a given point in time, we construct a list of executives meeting the above criteria. Then for each pair of executives from the supplier firm and the customer firm, we check whether they have studied at the same university (weak educational tie), at overlapping periods (educational tie) and whether any of their previous jobs were at the same company (weak employment tie) at the same time (employment tie). We allow for pairs of executives to count as multiple social connections if for instance they have both studied at the same university and worked at the same company prior to their current employment. We drop the pairs whose social connections are larger than 500.

Finally, we only keep pairs that at least have two-year observations in our sample, as we need within-pair variation to estimate the effects. We end up with 2,379 pairs of suppliers and customers which have variations in social connections over time, adding up to 11,990 pair-year observations.

### 3.3.2 Monetary Policy

To estimate the effect of monetary shocks on firm behaviors, we require a plausibly exogenous measure. In this paper, as pair-level data for firms is used to explore the impact of monetary policy, identification depends on the assumption that the aggregate variable, monetary shocks, has a considerable impact on individual firm pairs, but that these firm pairs have little effects on aggregate variables. Central banks do not formulate monetary policy based on individual firms' performance.

A usual measure of monetary tightening shocks applied in the financial literature, as in Oliner and Rudebusch (1996), Choi and Kim (2005) and Lin and Ye (2018), is the changes in the federal funds rate, provided that the federal funds rate is thought of as a good representative of the Reserve's policy stance (Bernanke and Blinder 1992, Christiano, Eichenbaum and Evans 1996). In the benchmark analyses, we want to use a similar measure. However, our sample extends from 2000 to 2016, including the recent crisis when the interest rate reached the zero lower bond (ZLB) and the fed implemented unconventional monetary policies. The effective fed funds rate can't represent the monetary stance in the ZLB period. Wu and Xia (2016) construct a shadow fed funds rate to summarize the overall stance of monetary policy for the ZLB period. We use the changes in the shadow fed funds rate as the measure of monetary tightening shocks. We normalize this measure to 0 mean and unit standard deviation. Figure 3.1 shows that this time series over the period 2000-2016. We can see that over the period 2004-2006 and 2014-2016, the index of monetary policy is larger than

Figure 3.1: Monetary Policy


This figure shows the evolution of monetary policy index over the period 2000-2016.

0, implying a monetary contraction period.

In the robustness section, we restrict our sample from 2000 to 2007 to exclude the impact of the 2008 financial crisis. We use two alternative measures of monetary policy. These two measures come from Romer and Romer (2004)[4] and Nakamura and Steinsson (2018). The first measure decomposes the changes in the federal fund rate using the Greenbook forecast, and the second measure develops the monetary policy index based on high frequency identification.

[4]This monetary policy index is extended to 2007 by Wieland and Yang (2019).

### 3.3.3 Sales and Trade Credit

In this paper, we mainly focus on the impact of monetary shocks on the transactions between suppliers and customers. The sales between them are the only pair-level variable available to us. As mentioned before, we focus on the relatively large sales. The median and mean ratios of the pair-level sales to suppliers' total sales in our sample are 0.15 and 0.20, respectively. In our sample, over 99% of the pair-level sales can account for at least 1% of the corresponding supplier' total sales, and almost 95% can account for at least 4%.

We propose trade credit as an important channel through which social connections affect the impact of monetary shocks on pair-level sales. As previously indicated, we do not observe trade credit at the pair level, we instead investigate the implications of this channel we would expect to hold if it is important. In this paper, suppliers' trade credit is defined as the ratio of the change in account receivable (*rect*) to total sales (*sale*). We multiply this ratio by 100. Supplier trade credit is positive if more goods are sold than bought and negative otherwise. Table 3.1 shows that the median and mean values of trade credit provided are 0.75 and 0.95, respectively, with a standard deviation of 6.40.

### 3.3.4 Social Capital

Social connections affect decision-making and performance because they can enhance trust as we discussed in the introduction. This implies that the level of regional social trust may have a substantial influence on the impact of social connections. Fukuyama ((1995), p. 27) and Putnam (2000), p. 19) define social trust as the expectation that human beings behave in a cooperative and honest way within a community and the extent to which reciprocity and trustworthiness can govern the interactions among humans. Putnam (2000) argues that an agent's social capital is more valuable with an increase in overall regional social capital. Framing this argument in our context, In regions with high social trust, social connections may become more valuable. We predict that social connections play a more important role in the transmission of monetary contraction shocks in regions with relatively high social trust. In our story, suppliers provide more trade credit to their socially connected customers in response to monetary contraction shocks. Thus, the level of social trust in the state where the suppliers are located in the key factor. In this paper, we use two measures of state-level social trust. One is Sen. Mike Lee's Social Capital Project[5] which combines

[5]For the detail of this index, check the website https://www.lee.senate.gov/public/index.cfm/scp-index.

seven dimensions. The other one is from Gallup[6], which reflects the degree that Americans express trust in their neighbors. Besides, we also want to see whether suppliers' social capital affects the impact of social connections. This firm-level index of social capital is constructed based on Lins et al (2017).

### 3.3.5 Other Controls

Some supplier- and customer-specific time-varying characteristics likely affect sales between suppliers and customers, and hence should be included as controls in all regressions. First, firm size has a considerable impact on sales. We capture supplier and customer firm size by the logarithm of total assets. Second, we also include supplier profitability to capture supplier differences in generating earnings and implementing efficient management. This variable is measured by the ratio of operating income before depreciation (*oibdp*) to total assets. Third, to control for the effect of suppliers' asset structures on their sales to the main customers, we use asset tangibility which is the ratio of net property, plant and equipment (*ppent*) to total assets (*at*). Finally, Mcmillan and Woodruff (1999) and Antras and Foley (2015) document that relationship length has a particularly important effect on suppliers' provision of trade credit. As a robustness check, we control for the distance between firms and their relationship. We use the address provided in the Compustat to calculate the distance between the suppliers and customers. As with the relationship, we use the number of years that the supplier and customer have been trading before 2000. To reduce the effects of possibly spurious outlines, we eliminatie the top and bottom 1% value of pair-level, supplier-level and customer-level variables.The statistical descriptions of these controls are also present in Table 3.1.

## 3.4 Empirical Strategy

We start our analyses by examining how social connections affect the impact of monetary contraction shocks on the pair-level sales. Then we provide some robustness checks to our baseline results. Finally, we extend our analyses in two ways. One way is to explain our benchmark results from the trade credit channel. The other is to check the heterogenous effects of social connections across regions with different levels of social trust.

[6]The data is from the website https://news.gallup.com/poll/123986/utah-south-dakota-best-places-lose-wallet.aspx

### 3.4.1 The Effects of Monetary Contractions on Sales

Existing studies show that firms in countries with higher levels of social trust suffer less during periods of liquidity crisis (e.g., Levine et al. 2018). To see the impact of social connections between firms on the propagation of monetary policy shocks, we estimate the following benchmark model:

$$\log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \cdot dummy\_sc_{i,j,t} \cdot MP_t + \beta_2 \cdot dummy\_sc_{i,j,t} + \beta_3 \cdot c\_size_{j,t} \\ \Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t} \tag{3.1}$$

$Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the measure of social connections between supplier $i$ and customer $j$ in year $t$, respectively. Our primary social connection measure is a dummy variable: $dummy\_sc_{i,j,t}$ equals 1 if there is one senior executive at the supplier firm that attended the same university or previously worked at the same company as at least one senior executive at the customer firm. $Sale_{i,t}$ is the total sales of supplier $i$ at time $t$. $MP_t$ is the index of monetary shocks in year $t$. $c\_size_{j,t}$ is the time-varying total assets of the customer firm. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects, respectively. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. The interaction term, $dummy\_sc_{i,j,t} \cdot MP_t$, captures the extent to which social connections moderate the sales between suppliers and customers when the economy experiences a monetary contraction shock.

We control for supplier's and customer's industry-fixed effects to capture the impact of time-invariant unobservable industry characteristics. However, firms might interact more, in sales and in drawing upon the same employees, with those firms that are in their vicinity. We alter the regression equation to check the robustness of our results by including pair fixed effects ($u_{i,j}$). Thus, our regressions exclude the impact of time-invariant unobservable pair characteristics which may influence sales as well as social connections between suppliers and customers. The impacts of $\mathbf{Pair}_{i,j}$, $u_{is}$ and $u_{js}$ are absorbed. We include time-varying suppliers characteristics plus time fixed effects[7] to account for trends and other shocks. For example, Gulen and Ion (2016) find that news-based policy uncertainty has a strong negative relationship with firm-level capital investment. Nguyen and Phan (2017) show that firms are less eager to make mergers and acquisitions (M&A) and spend more time completing M&A deals in face of policy uncertainty.

[7] Which is why we do not include $MP_t$ separately. Results are unchanged if we omit time fixed effects and include instead the full interaction of monetary shocks and social connections

Figure 3.2: Social Connections

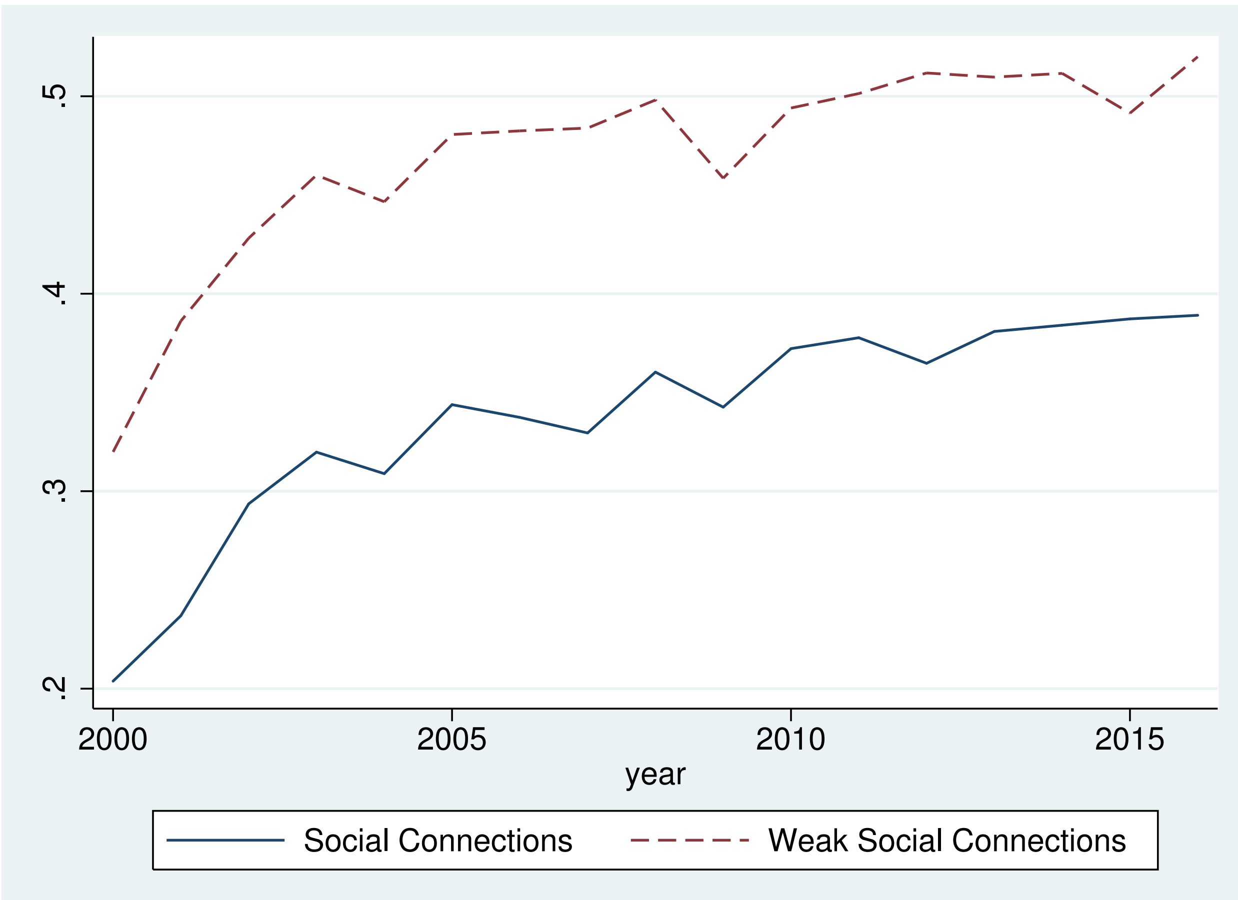



Figure 3.2 shows the evolution of social connections over 2000-2016. The solid line depicts the percentage of pairs that have at least one social connection, where employment and work ties must overlap, and the dash line the percentage of pairs that have a weak social connections, for which employment and work ties need not overlap.

In our benchmark analyses, we are interested in the interaction of monetary shocks and social connections on the sales between suppliers and customers. Appropriate measures of monetary contractions and social connections are vitally important for our analysis. To address these concerns, in the robustness section, we use two alternative measures of monetary policy and another measure of social connections using a broader definition to check the robustness of our baseline results. Besides, the social connections between downstream and upstream firms may just a result of short distance and long corporation duration. We add the interaction of monetary policy with them to exclude the impact of distance and duration.

Table 3.2 presents the estimated parameters from model (1) investigating whether social connections have a significant impact on the transmission of monetary shocks. We are interested in the interaction term, $dummy\_sc_{i,j,t} \cdot MP_t$, which captures the extent to which social connections moderate pair-level sales when the aggregate economy suffers a monetary shock. The solid line in Figure 3.2 denotes the percentage of socially connected pairs over the year 2000-2016. We can see that the fraction of the connected pairs increases from less than 25% in 2000 to almost 40% in 2016.

In column (i) and (ii), we control for supplier and customer industry-fixed effects. The only difference between these two columns is that we add time-fixed effects in column (ii). Thus, the impact of monetary policy is absorbed. We can see that the estimated coefficients on the interaction of social connection dummy and monetary contraction are positive and statistically significant at the 1% level. That is to say, sales between the connected pairs account for a greater share of suppliers total sales than the counterparts for the unconnected pairs during monetary shocks. We control for pair-fixed effects in column (iii) and (iv), and thus both industry-fixed effects, as well as $\mathbf{Pair}_{i,j}$, are absorbed. The regression in column (iv) controls for time-fixed effects like that in column (ii). We can see that the interaction terms keep their symbols and significance at 5% level at least. Our main results still hold.

Asset tangibility has considerable impacts on their sales according to the finance literature. To isolate the impact of supplier asset tangibility, we interact it with the index of monetary policy. For similar reasons, we also include the interactions of monetary contractions and suppliers' size, customers' size and suppliers' profitability in the regression to check the robustness of our result. The estimation results are present in the Appendix A3.1. We find that adding the interaction terms does not alter our result.

Table 3.2

**Monetary Policy and Sales**

| | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| $dummy\_sc * MP$ | 0.043*** | 0.043*** | 0.031*** | 0.028** |
| | (0.014) | (0.015) | (0.010) | (0.010) |
| MP | -0.017** | | -0.010* | |
| | (0.0081) | | (0.0057) | |
| $dummy\_sc$ | 0.075*** | 0.076*** | 0.0045 | 0.010 |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| CusSize | 0.037*** | 0.036*** | 0.057*** | 0.13*** |
| | (0.0063) | (0.0065) | (0.020) | (0.023) |
| SupSize | -0.067*** | -0.067*** | -0.12*** | -0.10*** |
| | (0.0044) | (0.0045) | (0.013) | (0.013) |
| Profitability | -0.10** | -0.10** | -0.038 | -0.035 |
| | (0.042) | (0.042) | (0.048) | (0.048) |
| Tangibility | 0.016 | 0.014 | 0.093 | 0.0020 |
| | (0.058) | (0.058) | (0.10) | (0.10) |
| Distance | 0.0049 | 0.0051 | | |
| | (0.0071) | (0.0071) | | |
| Relation | 0.015*** | 0.015** | | |
| | (0.0055) | (0.0055) | | |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | No | No |
| Customer_Industry | Yes | Yes | No | No |
| Pair | No | No | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 11,990 | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.08 | 0.08 | 0.66 | 0.66 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} * +\Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects respectively. In our analyses, we also include pair-level fixed effects to check the robustness, and thus the impacts of $\mathbf{Pair}_{i,j}$, $u_{is}$ and $u_{js}$ are absorbed. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

To gauge the economic magnitude of the effects, we use the regression result in column (i). The coefficient for the interaction term is 0.043. Thus, when the index of monetary shocks increases by one standard deviation, the ratio of the pair-level sales to suppliers' total sales will be 4.3% larger if the pair is socially connected than if not. Using pairs whose sales over suppliers' total sales is at the median level (0.15), the increase in between firm sales to supplier sales amounts to 0.65 percentage points ($15 \times 0.043$). For suppliers whose sales are located at the median level ($311 million), this reflects additional sales worth over $2 million ($311 \times 0.65\%$), assuming that total sales are unaffected.

Other than Wu and Xia (2016), Krippner (2016) measures the monetary stance using shadow interest rate (SSR). This rate is estimated from the shadow yield curve. As SSR reflects the impact of unconventional monetary policy on the longer-maturity interest securities, it has been an effective and popular index of monetary policy across conventional and unconventional environment. We use the changes in SSR as the measure to reflect the monetary stance and repeat our analyses. The results don't change, and we present them in Appendix A3.2.

### 3.4.2 Robustness Check

In this section, we provide three robustness checks to our benchmark results. First, we construct a weak social connection measure, and examine the impact of these new connection measure on the transmission of monetary policy shocks. This new measure doesn't need an overlapping-period social tie. Next, to address the concern that our results just hold for a particular measure of monetary policy, we use two alternative measure of monetary policy. Finally, we isolate the impact of distance and relationships on monetary policy transmissions.

#### New Social Connection Measure

In our baseline analyses, the suppliers and their customers are identified socially connected if their senior managers and board members ever attended a same educational institution or worked at a same third company for an overlapping period. This measure is thought of as an overlapping social connection measure (Ishii and Xuan (2014)). However, even if the members from the two parties attend a same educational institution or worked at a same third company at a different time, they are likely to be socially connected, especially for the educational network. For example, nowadays there is a lot of university alumni associations. People are likely to be interactive via these associations, especially for those who hold a senior position in one company. Next, we construct a new social connection measure

Table 3.3: **Weak Social Connections**

| | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| $wdummy\_sc * MP$ | 0.036*** | 0.036*** | 0.024** | 0.022** |
| | (0.014) | (0.014) | (0.0097) | (0.0097) |
| MP | -0.019** | | -0.011* | |
| | (0.0091) | | (0.0064) | |
| $wdummy\_sc$ | 0.072*** | 0.073*** | 0.043*** | 0.047** |
| | (0.015) | (0.015) | (0.014) | (0.014) |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | No | No |
| Customer_Industry | Yes | Yes | No | No |
| Pair | No | No | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 11,990 | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.08 | 0.08 | 0.66 | 0.66 |

**Note**: Statistical significance: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. This table presents the results of the following empirical specification:$\log \frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times wdummy\_sc_{i,j,t} \cdot MP_t + \beta_2 \times wdummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $wdummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company with one of the corresponding customer's senior managers and board members (weak connections). $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects respectively. In our analyses, we also include pair-level fixed effects to check the robustness, and thus the impacts of $\mathbf{Pair}_{i,j}$, $u_{is}$ and $u_{js}$ are absorbed. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

where we only require that members from the suppliers and their customers ever attended at a same educational institution or worked at a same company. This measure is called the weak social connection measure. In our sample, we can see that the mean value of weak social connection dummy is 0.47, implying that 47% of the observations are weakly socially connected. The dash line in Figure 3.2 denotes the percentage of socially connected pairs over the year 2000-2016. We can see that the fraction of the connected pairs increases from less than 35% in 2000 to around 50% in 2016.

We present the regression results with respect to the weak measure of social connections in Table 3.3. They are ordered as that in Table 3.2. We can still find that the coefficients on the interaction of weak social connection dummy and monetary contractions are positive and significant at the 5% level at least. Weak social connections can still facilitate the sales between supplier and customers when the aggregate economy comes across a monetary contraction shock.

To gauge the size of the impact of weak social connections on the propagation of monetary contraction shocks, we use the regression result in the first column as an example. When the economy suffers a one-standard-deviation increase in the index of monetary policy, the ratio of the pair-level sales over suppliers' total sales for the socially connected pairs will be 3.6% larger than that of the unconnected ones. Using the pairs whose sales over suppliers' total sales are in the median level (0.15) as an example, the sales for these pairs can account 0.54(0.015*3.6) percentage point more if the corresponding suppliers and customers are socially connected. For suppliers whose sales are located in the median level ($312 million), this means that they can sell $1.68 (312*0.54%) million more to their customers if they are socially connected. We can see that the impact of social connections is quite apparent and large. The fact that social connections facilitate sales in the presence of monetary recession shocks is robust to the weak social connections.

#### Alternative Measure of Monetary Contraction

This paper focuses on the social connections' impact on the transmissions of monetary policy. An appropriate measure of monetary policy is very important. In the baseline analyses, we construct the monetary policy shock using the shadow fed funds rate. In this subsection, we use two alternative measures of monetary policy to check the robustness of our results. These two measures come from Romer and Romer (2004) and Nakamura and Steinsson (2018). The first measure decomposes the changes in federal fund rate using the Greenbook forecast, and the second measure develops the monetary policy index based on high frequency identification. To avoid the zero-lower bound issues, following Ottonello and Winberry (2018), we use these two measures from 2000 to 2007.[8] The evolution of the new measures is shown in Figure 3.3. The aggregate economy suffers a monetary contraction over the period 2004-2006. The correlations between the three measures are listed in Table 3.4.

Table 3.4
**Correlation between Different Measures of Monetary Policy**

| | Shadow Rate | Romer&Romer | Nakamura&Steinsson |
|---|---|---|---|
| Shadow Rate | 1 | | |
| Romer&Romer | 0.90 | 1 | |
| Nakamura&Steinsson | 0.92 | 0.78 | 1 |

This table shows the correlation between the monetary policy measures from shadow rate, Romer and Romer (2004) and Nakamura and Steinsson (2018).

Then we use these new measures to repeat the benchmark analyses to check whether the regression results are robust to different measures. The results are present in Table 3.5. The first two columns use Romer and Romer's measure, and the rest two use Nakamura and Steinsson's. We control for supplier- and customer- industry fixed effects in all regressions and add time fixed effects in column (ii) and (iv). We present the results controlling for pair-fixed effects in the Appendix A3.3. The interactions of the new monetary policy measure and social connection dummy keep their significance at least at the 5% level. Thus, the sales between the upstream and downstream firms account more in the supplier's total sales if they are socially connected when the aggregate economy suffers a monetary contraction shock. Taking the results in column (i) into consideration, when the economy suffers a one-standard-deviation increase in the index of monetary policy, the ratio of the pair-level sales over suppliers' total sales for the socially connected pairs will be 5.1% larger than that of the unconnected ones. Using the pairs whose sales over suppliers' total sales are in the median level (0.15) as an example, the sales for these pairs can account 0.77(15*5.1%) percentage point more if the corresponding suppliers and customers are socially connected. For suppliers whose sales are located in the median level ($212 million)[9], this means that they can sell $1.62

[8]During the ZLB periods, these two measures can't captures firms' responses to unconventional monetary policy shocks.

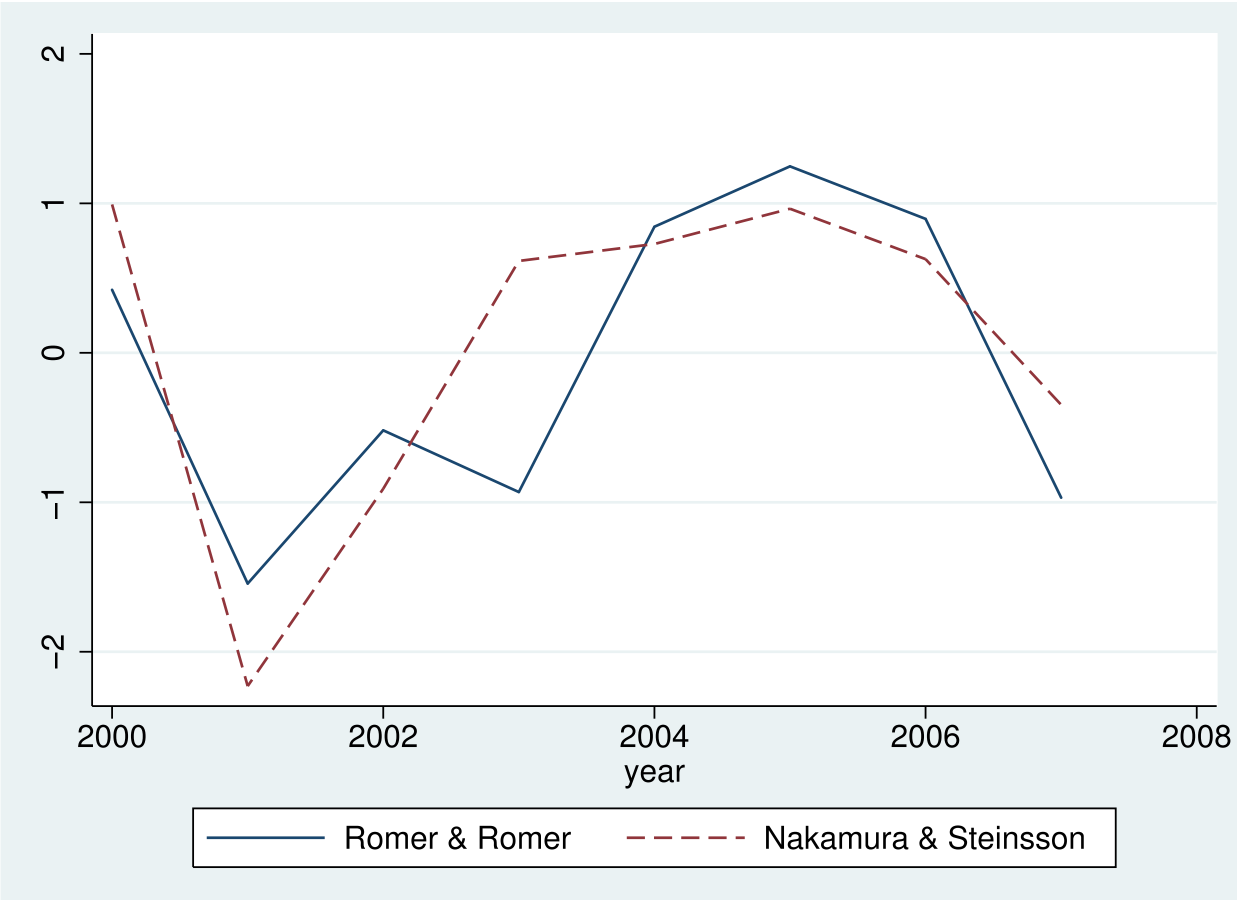
[9]In this section, our sample extends from 2000 to 2007. Thus, the median level of suppliers' total sales

Table 3.5
**Alternative Measure of Monetary Policy**

| | RR | | NS | |
|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) |
| $dummy\_sc * MP$ | 0.051*** | 0.052*** | 0.053** | 0.054** |
| | (0.020) | (0.019) | (0.021) | (0.021) |
| MP | -0.022** | | -0.024** | |
| | (0.010) | | (0.011) | |
| $dummy\_sc$ | 0.096*** | 0.099*** | 0.096*** | 0.099*** |
| | (0.024) | (0.024) | (0.024) | (0.024) |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | Yes | Yes |
| Customer_Industry | Yes | Yes | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 5,551 | 5,551 | 5,551 | 5,551 |
| Pairs | 1,407 | 1,407 | 1,407 | 1,407 |
| $Adj - R^2$ | 0.11 | 0.11 | 0.11 | 0.11 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. The first two columns use Romer and Romer's index, and the rest two use Nakamura and Steinsson's. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects, respectively. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Figure 3.3: Alternative Measures of Monetary Policy




This figure shows the evolution of two alternative measures of monetary policy over the period 2000-2007. The solid line is constructed by Romer and Romer (2004), while the dash line monetary policy time series comes from Nakamura and Steinsson (2018).

(212*0.77%) million more to their customers if they are socially connected. Here, we only repeat the results with respect to the social connection dummy. If we use the new measure of monetary policy to repeat the regressions with the weak social connection dummy, the results are much similar to the results in Table 3.3. We show these in Appendix A3.4. The coefficients on the interaction term are still positive and (weakly) significant. In conclusion, social connections help to facilitate the transactions between the upstream and downstream firms during periods of monetary contractions.

changes.

### The Role of Distance and Relationship

One concern may bias our benchmark results is that social connections may be just a result of short distance or long relationship. For example, the suppliers are likely to admit the graduates from a same university or employ the staff from a same third company with the customers located near them. The suppliers may share a similar preference in the graduate with their long-period customers. The social ties are then probably related to the distance between the upstream and downstream firms and the duration that the two parties have interacted with each other. In this subsection, we want to exclude the impact of pair-level distance or relationship to see whether social connections still have an impact on the transmission of monetary contraction shocks. We add the interactions of monetary contractions with the index of distance and relationship, respectively, in the empirical specification (1):

$$\log \frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \cdot dummy\_sc_{i,j,t} \cdot MP_t + \beta_2 \cdot dummy\_sc_{i,j,t} + \beta_3 \cdot c\_size_{j,t} + \Gamma * \mathbf{X}_{i,t}$$
$$+ \Theta * MP_t * \mathbf{Pair}_{i,j} + \Delta * \mathbf{Pair}_{i,j} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$$

where $\mathbf{Pair}_{i,j} \in \{distance_{i,j}, relationship_{i,j}\}$. $distance_{i,j}$ is the distance between the headquarters of the supplier and customer, and $relationship_{i,j}$ denotes the number of years that the supplier and customer have been trading before 2000. Other variables are the same as those in the empirical specification (1).

The estimation results are present in Table 3.6 where the first two columns add the interaction of monetary contractions and distance and corporation duration, respectively. And the last column excludes the effects of relationship and distance at the same time. We can see after isolating the impact of distance between the supplier and customer, the coefficients on the interaction terms are still significant at the 1% level. This implies that the sales within the connected pairs, on average, account more in the corresponding supplier's total sales, compared to the counterpart for the unconnected pairs. In detail, when the economy suffers a one-standard-deviation increase in the index of monetary policy, the ratio of the pair-level sales to suppliers' total sales for the socially connected pairs will be 4.4% larger than that for the unconnected ones. Using the pairs whose sales over suppliers' total sales are in the median level (0.15) as an example, the sales for these pairs can account 0.66(0.15*4.4) percentage point more if the corresponding suppliers and customers are socially connected. For suppliers whose sales are located in the median level ($311 million), this means that they can sell over $2 (312*0.66%) million more to their customers if they are socially connected. Column (ii) shows that if we add the interaction of monetary transactions and relationship

Table 3.6

**Distance and Relationship**

| | (i) | (ii) | (iii) |
|---|---|---|---|
| dummy_sc*MP | 0.044*** | 0.043*** | 0.44*** |
| | (0.014) | (0.014) | (0.14) |
| dummy_sc | 0.075*** | 0.075*** | 0.075*** |
| | (0.015) | (0.015) | (0.015) |
| MP | -0.017** | -0.018** | -0.019** |
| | (0.0081) | (0.0084) | (0.0084) |
| Distance*MP | 0.0070 | | 0.0070 |
| | (0.0072) | | (0.0071) |
| relationship*MP | | 0.0047 | 0.0048 |
| | | (0.0064) | (0.0065) |
| Controls | Yes | Yes | Yes |
| Fixed Effect | | | |
| Supplier_Industry | Yes | Yes | Yes |
| Customer_Industry | Yes | Yes | Yes |
| Observations | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.08 | 0.08 | 0.08 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \cdot MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Gamma * \mathbf{X}_{i,t} + \Theta * MP_t * \mathbf{Pair}_{i,j} + \Delta * \mathbf{Pair}_{i,j} + u_{i,j} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $MP_t$ is the index of monetary contractions in year $t$. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ denotes the distance between the supplier and customer or the duration that the downstream firms become the main customers of the supplier. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

to control for the impact of relationship, our results doesn't change. Besides, controlling for pair-fixed effects doesn't alter the results. We report these results in the Appendix A3.5. In conclusion, our benchmark results are robust to the model with the impact of distance and relationship excluded.

## 3.5 Extensions

In this section, first, we explain the benchmark results from the trade credit channel. Second, we exploit regional variations in social trust to explore the heterogenous effects of social connections.

### 3.5.1 The Trade Credit Channel

Why do social connections affect the transmission of monetary recession shocks to the transactions between suppliers and customers? And via which channel do social connections affect the impact of monetary policy on the sales within each transaction pair?

In face of monetary contractions, firms may come across more difficulties and cost more to borrow from financial intermediaries like commercial banks. Trade credit from the suppliers can be an important substitute of credit for the downstream firms. The transactions between suppliers and customers will rely on trade credit more during periods of monetary recessions. The customers can choose to sign trade credit contracts with their suppliers, and the contract should be implemented in the near future. The asymmetric information problem between the two parties will incur a hold-up problem. The suppliers are not sure about customers' ability to repay the debt, as they don't know their customers' profitability, management, and other financial conditions completely. Social connections will help to mitigate the hold-up problem by improving the efficiency of information transfer and lowering the cost of gathering information. Thus, suppliers are more likely to trust the socially connected customers, which makes suppliers have more incentives offer more trade credit to their customers.

Motivated by the arguments above, we expect that suppliers will extend more trade credit to their connected customers in face of monetary recession shocks, as they know the connected ones' financial conditions better and trust the connected customers more. To test this hypothesis directly, we should know the trade credit within each pair over time. Unfortunately, we have no information about the pair-level trade credit. We will test two indirect conjectures instead. First, if the connected pair uses more trade credit in face of monetary contractions, customers will accumulate account payable more. Thus, the sales should be more sensitive to customers' changes in account payable for the connected pairs. We estimate this conjecture by estimating the following regression specification:

$$log(\frac{Sale_{i,j,t}}{Sale_{i,t}}) = \theta_0 + \theta_1 * dummy\_sc_{i,j,t} * MP_t * \frac{apch_{j,t}}{lct_{j,t}} + \theta_2 * dummy\_sc_{i,j,t} * MP_t + \theta_3 * dummy\_sc_{i,j,t} * \frac{apch_{j,t}}{lct_{j,t}}$$

$$+\theta_4 * \frac{apch_{j,t}}{lct_{j,t}} * MP_t + \theta_5 * dummy\_sc_{i,j,t} + \theta_6 * \frac{apch_{j,t}}{lct_{j,t}}$$
$$+\theta_7 * size_{i,t} + \theta_8 * c\_size_{j,t} + u_{i,j} + u_t + \epsilon_{i,j,t} \qquad (2)$$

where $apch_{j,t}$ is supplier $j$'s changes in account payable, and $lct_{j,t}$ denotes supplier $j$'s total current liabilities. Other variables are the same as those in equation (1). We also further control time-fixed effects and use a weak social connection dummy to check the robustness. The triple interaction term, $dummy\_sc_{i,j,t} * MP_t * \frac{apch_{j,t}}{lct_{j,t}}$, reflects the sensitivity of the connected pair's sales to the corresponding customer's trade credit payables during periods of monetary contractions. A positive value of the coefficient ($\theta_1$) is consistent with our prediction.

Table 3.7 present the estimation results. We concentrate on the triple interaction term, $dummy\_sc_{i,j,t} * MP_t * \frac{apch_{j,t}}{lct_{j,t}}$, which reflects the sensitivity of the pair-level sales to the changes in corresponding customers' account payable in face of monetary contractions. In the first two columns, we use the social connection dummy in Section 3.4.1, while social connections in the rest two columns refer to weak social connection dummy used in the robustness check.

The only difference between the first two columns is that we control for time-fixed effects in the second column. The impact of monetary policy is absorbed in the second column. First, we can see that the coefficients on the interaction of social connection dummy and monetary contractions are still positive and keep their significance at 5% level. This implies that when we keep suppliers' ratio of changes in account payable scaled over total current liabilities at the mean level[10], the socially connected pairs' sales will account more in the corresponding supplier's total sales compared to the unconnected ones' when the aggregate economy when the aggregate economy comes across a monetary contraction shock. These estimation results are consistent with our benchmark results. More importantly, we can see

[10]In Table 3.7, we normalize the changes in account payable scaled by total current liabilities to 0 mean.

Table 3.7
**Trade Credit Channel I**

| | Dummy | | Weak Dummy | |
|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) |
| $dummy\_sc * MP * \frac{apch}{lct}$ | 0.32** | 0.32** | 0.29** | 0.30** |
| | (0.13) | (0.13) | (0.13) | (0.13) |
| $dummy\_sc * MP$ | 0.031*** | 0.028** | 0.024** | 0.022** |
| | (0.011) | (0.011) | (0.011) | (0.010) |
| $dummy\_sc * \frac{apch}{lct}$ | 0.24 | 0.21 | 0.25 | 0.22 |
| | (0.15) | (0.15) | (0.15) | (0.15) |
| $MP * \frac{apch}{lct}$ | -0.029 | -0.036 | -0.020 | -0.029 |
| | (0.066) | (0.067) | (0.066) | (0.068) |
| $dummy\_sc$ | -0.0082 | -0.0017 | 0.035** | 0.039*** |
| | (0.017) | (0.017) | (0.015) | (0.015) |
| $\frac{apch}{lct}$ | -0.087 | -0.063 | -0.093 | -0.067 |
| | (0.074) | (0.076) | (0.074) | (0.076) |
| MP | -0.0089 | | -0.010 | |
| | (0.0061) | | (0.0068) | |
| Controls | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | |
| Time | No | Yes | No | Yes |
| Pair | Yes | Yes | Yes | Yes |
| Observations | 11,004 | 11,004 | 11,004 | 11,004 |
| Pairs | 2,212 | 2,212 | 2,212 | 2,212 |
| $Adj - R^2$ | 0.66 | 0.66 | 0.66 | 0.66 |

**Note**: Statistical significance: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. This table presents the results of the following empirical specification: $log(\frac{Sale_{i,j,t}}{Sale_{i,t}}) = \theta_0 + \theta_1 * dummy\_sc_{i,j,t} * MP_t * \frac{apch_{j,t}}{lct_{j,t}} + \theta_2 * dummy\_sc_{i,j,t} * MP_t + \theta_3 * dummy\_sc_{i,j,t} * \frac{apch_{j,t}}{lct_{j,t}} + \theta_4 * \frac{apch_{j,t}}{lct_{j,t}} * MP_t + \theta_5 * dummy\_sc_{i,j,t} + \theta_6 * \frac{apch_{j,t}}{lct_{j,t}} + \theta_7 * MP_t + \gamma * \mathbf{X}_{i,t} + u_{i,j} + \epsilon_{i,j,t}$, where $apch_{j,t}$ is supplier $j$'s changes in account payables and $lct_{j,t}$ denotes supplier $j$'s total current liabilities. Other variables are same as the one in Table 3.2. In the first two columns, the social connection dummy is same as that in Table 3.2. The weak social connection dummy in the rest two columns refers to the one in Table 3.3 (weak connections). Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

that the coefficients on the triple interaction term are positive and statistically significance at the 5% level, consistent with our expectation. For the connected pairs, when the customers use more trade credit, the pair-level sales will account more compared to the unconnected pairs when there exists a monetary contraction shock. Customers will ask for more trade credit from their connected suppliers to pay their transactions. Our estimation result is robust if we use weak social connection dummy as the explanatory variable. The estimation results are shown in the rest two columns.

We use the regression result in the first column to understand the extent to which customers' $\frac{apch}{lct}$ increases the sales within the connected pairs when the economy suffers a one-standard-deviation monetary contraction shock. The sales within the connected pairs will account 3.1% more in the supplier's total sales than the unconnected ones during periods of monetary recessions when customers' $\frac{apch}{lct}$ stays at the mean level. If the customers' changes in account payables occupy 1 percentage point more total current liabilities, the interaction of social connection dummy and monetary recession will increase by 0.32%, corresponding to 10.3% of the mean level of the interaction on the sales (3.1%). We have that the sales of the connected pair are quite sensitive to the customers' $\frac{apch}{lct}$.

Next, we use suppliers' total trade credit instead of pair-level trade credit to explore whether social connections affect suppliers' provision of trade credit in total when they suffer a monetary recession shock. We construct a supplier-level index of social connections by calculating the mean of pair-level social connections for one supplier in the corresponding year. That is:

$$sc_{i,t} = Mean_{i,t}(dummy\_sc_{i,j,t})$$

$sc_{i,t}$ reflects customer $i$'s ratio of connected customers during period $t$.

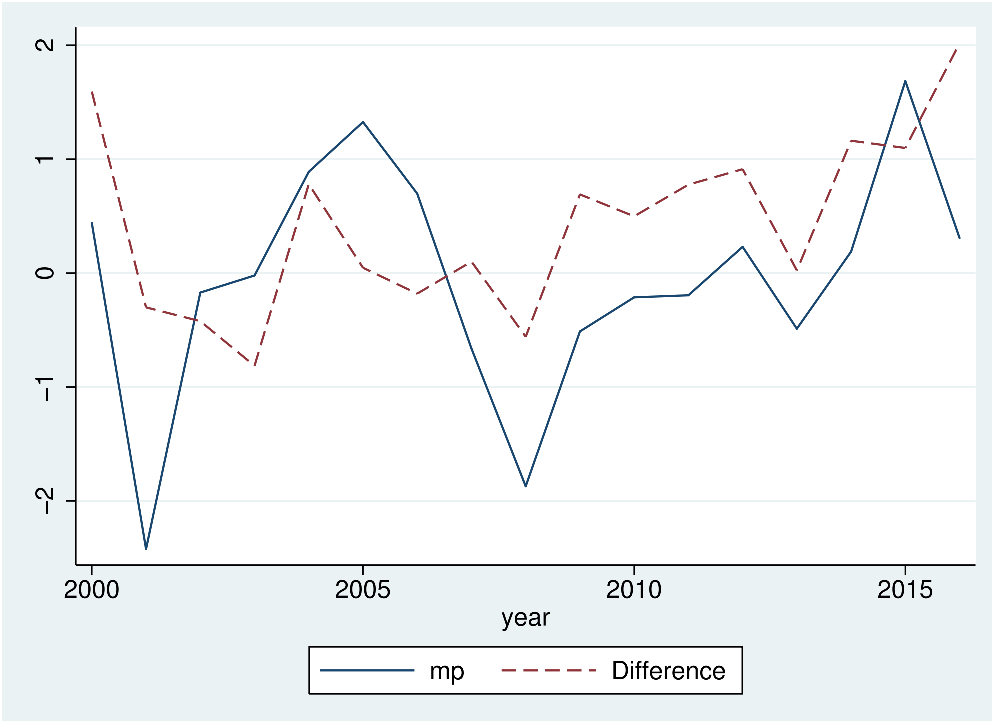
Existing studies suggest that firms will issue more trade credit to their customers when they suffers a monetary contraction shock.[11] We conjecture that social connections amplify this impact and test this conjecture by estimating the following regression equation:

$$Rech_{i,t}/sale_{i,t} = \alpha_0 + \alpha_1 * sc_{i,t} * MP_t + \alpha_2 * sc_{i,t}$$

$$+\gamma X_{i,t} + u_i + u_t + \epsilon_{i,t} \qquad (3)$$

[11] Choi and Kim (2005) find that both account receivable and payable increases with monetary contractions. Mateut et al. (2006) find that firms use more trade credit than bank credit in response to a monetary contraction shock.

Figure 3.5: Suppliers' Change in Account Receivable




The solid line is the evolution of monetary policy index. The dash line is the difference of the mean value of suppliers' changes in account receivable between the "connected" and "unconnected" group over 2000-2017. Here "connected" means that at least one senior managers or board member of the supplier even attended the same educational institutions or worked at the same company for an overlapping time with the counterparts of the customer.

$Rech_{i,t}$ is changes in supplier $i$'s account receivable in year $t$. $sale_{i,t}$ denotes supplier $i$'s total sales.

Other variables are same as those in estimation equation (1). We also control firm- and time-fixed effects. The key variable of interest is the coefficient ($\alpha_1$) on the interaction term between the social connections and monetary policy. According to the above argument, during periods of monetary contractions, the suppliers will extend more trade credit in total if they are socially connected with their main customers. Thus, a positive coefficient ($\alpha_1$) would be in favor of our predictions.

Some preliminary evidences are shown in Figure 3.5. We call suppliers' changes in total account receivables scaled by their sales $TradeCredit$. The solid line is the evolution of monetary policy, while the dash line denotes the difference of $TradeCredit$ between the connected and unconnected ones. We can see that the difference co-moves with monetary policy and the correlation between them are high (0.45). Using the empirical equation (3), we investigate whether suppliers' $TradeCredit$ increases more in response to a monetary contraction shock if they are socially connected with their main customers. The estimation results are present in the first two columns of Table 3.8. We add time-fixed effects in the regressions and thus the level effects of monetary policy are absorbed. In the second column, pair fixed effects are controlled. We construct a supplier-level index of weak social connections by calculating the firm-year mean of weak social connection dummy, and then repeat the analyses. The results are in Appendix 3.6.

We are interested in the coefficients on the interaction term, $sc_{i,t} * MP_t$, which captures the extent to which social connections affect the transmissions of monetary policy shocks to suppliers' $TradeCredit$. We have that the coefficients on the interaction term are both positive and weakly significant at the 10% level at least. Thus, as expected, suppliers provide more trade credit if they are socially connected with their main customers when coming across monetary contractions. Use the estimation result in the first column as an example. When the aggregate economy suffers a one-standard-deviation increase in monetary contractions, the suppliers will on average extend 0.33 percentage point more trade credit to their customers if the suppliers are socially connected with one of their main customers. This economic magnitude corresponds to 35% of the mean of the ratio of the change in account receivable to total sales (0.95). Social connections have a considerable influence on the suppliers' provision of trade credit. Our result is robust to the weak social connections.

However, due to the shortage of pair-level account receivables, there exist limitations to our arguments. The supplier may think that the sales to the connected customers are stable even if they suffer a credit contraction shock and providing more trade credit won't get much marginal benefit. They pay much attention to the transactions to the unconnected ones and provide more trade credit to them. Thus the increasing trade credit may be incurred by the increasing trade credit extended to suppliers' other customers.

To deal with the limitations and identify the impact of social connections on suppliers' trade credit, we impose another examination. If suppliers which have tighter social connections provide more trade credit to their customers in face of credit contractions, suppliers should provide more trade credit in total if their main customers depend on more external finance or have a higher liquidity need. To check this prediction, we divide our sample into two subsamples by customers' industry-level external financial dependence or liquid needs.

Table 3.8

**Trade Credit Channel II**

| | | | External Financial Dependence | | Liquidity Needs | |
|---|---|---|---|---|---|---|
| | Connections | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| sc*MP | 0.33** | 0.32* | 0.63** | -0.052 | 0.57** | 0.057 |
| | (0.16) | (0.17) | (0.27) | (0.18) | (0.29) | (0.18) |
| sc | 0.45*** | 0.29 | 0.61** | 0.25 | 0.58** | 0.28 |
| | (0.16) | (0.23) | (0.26) | (0.19) | (0.27) | (0.19) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes |
| Supplier_Industry | Yes | No | Yes | Yes | Yes | Yes |
| Supplier | No | Yes | No | No | No | No |
| Observations | 9,335 | 9,335 | 4,629 | 4,726 | 4,285 | 5,070 |
| Supplier | 1,473 | 1,473 | 780 | 693 | 731 | 756 |
| $Adj-R^2$ | 0.04 | 0.12 | 0.05 | 0.04 | 0.05 | 0.04 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The regression equation is: $Rech_{i,t}/sale_{i,t} = \alpha_0 + \alpha_1 * sc_{i,t} * MP_t + \alpha_2 * sc_{i,t} + \gamma * \mathbf{X}_{i,t} + u_i + u_t + \epsilon_{i,t}$. $Rech_{i,t}$ is changes in supplier $i$'s account receivables in year $t$. $sale_{i,t}$ denotes supplier $i$'s total sales. The first two columns use all observations in our sample. In the median two columns, we divide the whole sample into two subsamples based on customers' industry-level external finance dependence. In the last two columns, we divide the whole sample into two subsamples based on customers' industry-level liquid needs which is equal to the ratio of short-term debt over sales. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

The constructions of industry-level external financial dependence and liquid needs will be discussed in the following section.

We use regression equation (3):

$$Rech_{i,t}/sale_{i,t} = \alpha_0 + \alpha_1 * sc_{i,t} * MP_t + \alpha_2 * sc_{i,t}$$

$$+\gamma X_{i,t} + u_i + u_t + \epsilon_{i,t}$$

We expect that the value of $\alpha_1$ for the subsample which has a higher external financial dependence or a higher liquid need is larger than the counterparts which need less external financing or liquids.

We describe the process related to trade credit dependence in detail and the one with respect to liquidity needs follow the same procedure. First, we construct an industry-level index of trade credit dependence following Rajan and Zingales (1998)[12]. Next, we define supplier-level customers' external financial dependence using the mean of all customers' external financial dependence for each supplier. That is:

$$EFD_i = Mean_i(EFD_{i,j})$$

where $EFD_i$ is supplier $i$'s customer external financial dependence and $EFD_{i,j}$ is customer $j$'s industry-level external financial dependence.

The observations in the original sample are divided into two groups based on customers' industry-level external financial dependence. We call the group whose customers' dependence is above the median value "High" external financial dependence group and the other one "Low" external financial dependence group. Third, we repeat the regression with respect to suppliers' $TradeCredit$ for both groups and see whether the coefficients on the interaction term are significantly different. Fourth, I construct the industry-level liquidity needs[13] and repeat the three steps above.

[12]We use the data from Compustat-U.S. First, we calculate the sum of firms' external financing and capital expenditures over the relevant periods and then computes the ratio of external financing and capital expenditures. Second, we use the median level of the distribution of this ratio within the corresponding industry as the industry-level external financial dependence. In our exercise, we restrict the sample from 1979 to 1999 because the sample we use in the regressions starts from 2000. If the sample is extended to 2009 or 2017 and we construct the measure using the same procedures as before, we find that the former measure is highly correlated with the latter two. In this paper, we divided manufacturing firms into 20 industries based on two-digit SIC code.

[13]Here we define liquidity needs as the ratio of short-term debt over sales.

The estimation results are shown in the last four columns of Table 3.8. Column (iii) and (iv) present the regressions for the high and low external financial dependence groups, respectively. We can see the coefficient on the interaction for the high group is 0.63, strongly significant at the 5% level. The socially connected suppliers whose customers depend on trade credit more will extend 0.63 percentage point more trade credit in total when the economy comes across a one-standard-deviation monetary contraction shock. As for the group with low trade credit dependence, the impact is not significant. When we divide the original sample in accordance with industry-level liquidity needs, the results are similar. The effects of social connections in the group whose customers have a relatively larger liquidity need are stronger than the group with a low liquidity need.

In this section, first, we find that when customers use more trade credit in the transactions, the socially connected pairs' sales will increase more during monetary contraction periods. Second, if the customers are located in the industry which needs more trade credit or liquidity, the corresponding connected suppliers provide more trade credit in total. These two findings help us to confirm the argument that social connections can increase suppliers' provision of trade credit in the presence of monetary contractions. Thus the trade credit channel works to explain why social connections facilitate the pair-level sales during periods of monetary recessions.

### 3.5.2 Heterogeneous Effects in Social Capital

In our analyses above, we argue that social connections help to mitigate the negative effects of monetary contractions on sales between suppliers and customers via trade credit channel. Next we depend on the empirical specification (1) to test an additional implication of this point. Putnam (2000) argues that an agent's social capital is more valuable with an increase in overall regional social capital. Based on this point, Lins et al. (2017) show that high-CSR firms in states with higher levels of social trust have higher stock returns when the overall trust suffers negative shocks. Framing the argument in our analyses, social connections work by enhancing the sense of trust, which implies that social connections may have larger impacts in regions where the trust between different agents is high. As our mechanism works via suppliers' provision of trade credit, the social trust of the state where the supplier is located is important because it can affect firms' decision on trade credit provided. We test this implication using a similar procedure in the argument for the trade credit channel. First, we divide our sample into two subsamples according to the social trust of the state where the supplier's headquarter is located. The two measures of social trust come from Sen. Mike Lee's Social Capital Project and Gallup, respectively. We call the group whose suppliers' state-level social trust is below the median value the "Low" trust group, and the other one the "High" trust group. Second, we repeat the regression using the empirical specification (1) and see whether the coefficients on the interaction term are different. According to the discussion above, social connections should decrease the negative effects of monetary contractions more in the group with higher social trust. A larger $\beta_1$ for the high group is in favor of our prediction.

The estimation results are present in the first four columns of Table 3.9. In the first two columns, we divide the sample into two subsamples based on the suppliers' state-level social trust from Sen. Mike Lee's Social Capital Project. We get that the coefficient on the interaction term for the group where the suppliers are located in states with higher social trust is 0.045, significant at the 1% level. This means that the sales of the pairs whose suppliers are in the high-social-trust state will account 0.68 (15*0.045) percentage point more to their socially connected customers than that of the unconnected ones. As for the suppliers located in states with lower social trust, the coefficient on the interaction term is 0.011, smaller than the counterpart for the high-social-trust group but not significant. These results are consistent with our prediction. Furthermore, if we divide our sample according to the index of social trust from Gallup, the results still stand by our predictions. In conclusion, social connections can ease the negative impact of monetary contraction on pair-level sales, especially for the suppliers who are located in states with higher levels of social trust.

In the above analysis, we consider the heterogeneous effects of social connections from the angle of suppliers. Next we test whether the impact of social connections is heterogeneous in customers' social capital. According to our argument, social connections enhance the impact of social capital. Thus, social connections should have a larger impact if the customers have higher levels of social capital. To test this hypothesis, we construct suppliers' social capital based on Lins et al. (2017). Then we divide our sample into two subgroups. We call the group whose customer-level social trust is below the median value "Low" trust group and the other one "High" trust group. Finally, we repeat the regression using the empirical specification (1), and see whether the coefficients on the interaction term are different. The estimation results are shown in the last two columns of Table 3.9. We can see that the coefficient on the interaction term for the group where the suppliers have higher social trust is 0.034, significant at the 5% level. This means that the sales of the pairs whose suppliers have higher social trust will account 0.51 (15*0.034) percentage point more to their socially

Table 3.9
**Heterogeneous Effects**

| | Trust1 | | Trust2 | | Trust3 | |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| $dummy\_sc * MP$ | 0.011 | 0.045*** | 0.0096 | 0.046*** | 0.016 | 0.034** |
| | (0.014) | (0.015) | (0.014) | (0.015) | (0.015) | (0.014) |
| $dummy\_sc$ | 0.025 | -0.0033 | 0.024 | -0.0024 | -0.0023 | 0.029 |
| | (0.024) | (0.021) | (0.024) | (0.021) | (0.019) | (0.025) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes |
| Pair | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,663 | 6,327 | 5,649 | 6,341 | 5,846 | 5,840 |
| Pairs | 1,152 | 1,227 | 1,153 | 1,226 | 1,149 | 1,151 |
| $Adj - R^2$ | 0.66 | 0.66 | 0.67 | 0.67 | 0.67 | 0.66 |

**Note**: Statistical significance: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$.This table presents the results of the following empirical specification: $log(\frac{Sale_{i,j,t}}{Sale_{i,t}}) = \beta_0 + \beta_1 * dummy\_sc_{i,j,t} * MP_t + \beta_2 * dummy\_sc_{i,j,t} + \beta_3 * MP_t + \beta_4 * c_size_{j,t} + \gamma * \mathbf{X}_{i,t} + u_{i,j} + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. In addition, we add suppliers' vector of controls (suppliers' size, profitability and asset tangibility) in the regression to check the robustness of our result. We control for pair-fixed effects, $u_{i,j}$ and time-fixed effect $u_t$. We divide the sample into two subsamples based on the state-level social trust. Here "Low" means that the suppliers are located in a state with low social trust while "High" means that the suppliers are in the state with high social trust. In the first two columns, "Trust1" denotes the social trust constructed from Sen. Mike Lee's Social Capital Project and "Trust2" represents the social trust constructed by Gallup in 2009. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

connected customers than that of the unconnected ones. As for the customers with lower social capital, the coefficient on the interaction term is 0.016, smaller than the counterpart for the high-social-trust group but not significant. These results are consistent with our prediction.

If we consider the heterogenous effects of weak social connections across regions with different levels of social trust, our results still hold other than the results related to customers' social capital. We present these results in Appendix A3.7.

## 3.6 Conclusions

This paper investigates the impact of social connections between upstream and downstream firms on the transmissions of monetary contraction shocks. Using the transaction data between suppliers and customers, we first find that monetary policy contraction shocks have a negative impact on the pairs' sales between suppliers and customers, and social connections can reduce these negative effects. And this result is not only robust to the empirical specifications where more controls or time-fixed effects are included, but also robust to an alternative measure of monetary policy and social connections.

We argue that social connections work via adjusting firms' trade credit. Because we have no access to the pair-level data about trade credit, we test two indirect conjectures instead. First, the pair-level sales are more responsive to the changes in customers' account payable if social connections can affects the sales via the trade credit channel. The regression shows that the coefficients on the triple interaction of customers' trade credit received, monetary contraction and social connection dummy are statistically significant and positive, which is consistent with our first conjecture. Second, suppliers whose customers have a higher trade credit dependence or liquidity need extend more trade credit in total. To test this conjecture, we divide our sample into two groups based on suppliers' industry-level trade credit dependence and liquidity needs. When we use the ratio of changes in suppliers' account receivable over total assets as the dependent variable, the coefficients on the interaction of social connection dummy and monetary contractions for the group with higher trade credit dependence or liquidity needs will be larger than the counterparts for the other group. This confirms our second conjecture.

Finally, we build on our benchmark results to assess an additional implication of the view that social connections affect the transmission of monetary contraction shocks because these connections can enhance the sense of trust. Social connections have a larger impact in the state with higher social trust. We divide our sample into two subsamples based on two measures of social trust. The coefficient on the interaction of monetary contractions and social connections for the group with higher social trust is significant and larger than the counterpart with lower social trust. This result is in favor of our predictions.

In conclusion, the sales between suppliers and their main customers will decrease when the aggregate economy suffers a monetary contraction shock and social connections between the two parties can help to mitigate the negative impact via increasing suppliers' provision of trade credit.

## 3.7 Appendix

Appendix A3.1

**Monetary Policy and Sales**

| | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| $dummy\_sc * MP$ | 0.039** | 0.040** | 0.032*** | 0.030*** |
| | (0.015) | (0.016) | (0.011) | (0.011) |
| MP | -0.015* | | -0.0091 | |
| | (0.0082) | | (0.0061) | |
| $dummy_sc$ | 0.075*** | 0.076*** | 0.0043 | 0.0098 |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | No | No |
| Customer_Industry | Yes | Yes | No | No |
| Pair | No | No | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 11,990 | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.08 | 0.08 | 0.66 | 0.66 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} * +\Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + \beta_4 * c\_size_{j,t} * MP_t + \beta_5 * \mathbf{X}_{i,t} * MP_t + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects respectively. In our analysis, we also include pair-level fixed effects to check the robustness and then the impacts of $\mathbf{Pair}_{i,j}$, $u_{is}$ and $u_{js}$ are absorbed. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Standard errors are clustered at the pair and year level. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.2: **Alternative Shadow Federal Funds Rate**

| | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| $dummy\_sc * MP$ | 0.029** | 0.028*** | 0.024** | 0.021** |
| | (0.014) | (0.014) | (0.0099) | (0.0099) |
| MP | -0.016** | | -0.012** | |
| | (0.0080) | | (0.0055) | |
| $dummy\_sc$ | 0.075*** | 0.075*** | 0.0046 | 0.010 |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | No | No |
| Customer_Industry | Yes | Yes | No | No |
| Pair | No | No | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 11,990 | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.08 | 0.08 | 0.66 | 0.66 |

**Note**: Statistical significance: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} * +\Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. Here we use the changes in Krippner's SSR. $c\_size_{j,t}$ is the time-variant total assets of customer.$\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects respectively. In our analysis, we also include pair-level fixed effects to check the robustness and then the impacts of $\mathbf{Pair}_{i,j}$, $u_{is}$ and $u_{js}$ are absorbed. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.3

**Alternative Measure of Monetary Policy**

| | RR | | NS | |
|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) |
| $dummy\_sc * MP$ | 0.038*** | 0.038*** | 0.030* | 0.031** |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| MP | -0.018** | | -0.021*** | |
| | (0.010) | | (0.0080) | |
| $dummy\_sc$ | 0.072** | 0.084*** | 0.073** | 0.084*** |
| | (0.030) | (0.030) | (0.030) | (0.030) |
| Fixed Effect | | | | |
| Pair | Yes | Yes | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 5,551 | 5,551 | 5,551 | 5,551 |
| Pairs | 1,407 | 1,407 | 1,407 | 1,407 |
| $Adj - R^2$ | 0.67 | 0.67 | 0.67 | 0.67 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{i,j} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. The first two columns use Romer and Romer's measure, while the rest two use Nakamura and Steinsson's. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{i,j}$ is pair-fixed effects respectively. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.4

**Weak Social Connections**

| | RR | | NS | |
|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) |
| $dummy\_sc * MP$ | 0.042** | 0.042** | 0.042** | 0.044** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| MP | -0.023* | | -0.027** | |
| | (0.013) | | (0.012) | |
| $dummy\_sc$ | 0.076*** | 0.079*** | 0.077*** | 0.080*** |
| | (0.022) | (0.022) | (0.022) | (0.022) |
| Fixed Effect | | | | |
| Supplier_Industry | Yes | Yes | Yes | Yes |
| Customer_Industry | Yes | Yes | Yes | Yes |
| Time | No | Yes | No | Yes |
| Observations | 5,551 | 5,551 | 5,551 | 5,551 |
| Pairs | 1,407 | 1,407 | 1,407 | 1,407 |
| $Adj - R^2$ | 0.11 | 0.11 | 0.11 | 0.11 |

**Note**: Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \times MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Delta * \mathbf{Pair}_{i,j} + \Gamma * \mathbf{X}_{i,t} + u_{is} + u_{js} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company with one of the corresponding customer's senior managers and board members (weak connections). $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ is a vector of time-invariant pair-level characteristics. $u_{ic}$ and $u_{jc}$ are supplier's and customer's industry-fixed effects respectively. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.5

**Distance and Relationship-Pair-Fixed Effects**

| | (i) | (ii) | (iii) |
|---|---|---|---|
| $dummy\_sc * MP$ | 0.031*** | 0.031*** | 0.31*** |
| | (0.010) | (0.010) | (0.10) |
| $dummy\_sc$ | 0.0045 | 0.0045 | 0.0044 |
| | (0.016) | (0.016) | (0.016) |
| MP | -0.010* | -0.0096** | -0.0096 |
| | (0.0057) | (0.0058) | (0.0058) |
| Distance*MP | 0.0091* | | 0.0091* |
| | (0.0051) | | (0.0050) |
| relationship*MP | | -0.0012 | -0.0012 |
| | | (0.0033) | (0.0034) |
| Controls | Yes | Yes | Yes |
| Fixed Effect | | | |
| Pair | Yes | Yes | Yes |
| Observations | 11,990 | 11,990 | 11,990 |
| Pairs | 2,379 | 2,379 | 2,379 |
| $Adj - R^2$ | 0.66 | 0.66 | 0.66 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.This table presents the results of the following empirical specification: $log\frac{Sale_{i,j,t}}{Sale_{i,t}} = \beta_0 + \beta_1 \times dummy\_sc_{i,j,t} \cdot MP_t + \beta_2 \times dummy\_sc_{i,j,t} + \beta_3 \times c\_size_{j,t} + \Gamma * \mathbf{X}_{i,t} + \Theta * MP_t * \mathbf{Pair}_{i,j} + \Delta * \mathbf{Pair}_{i,j} + u_{i,j} + u_t + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $dummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. In the first three columns, we use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company for an overlapping period with one of the corresponding customer's senior managers and board members. $MP_t$ is the index of monetary contractions in year $t$. $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. $\mathbf{Pair}_{i,j}$ denotes the distance between the supplier and customer or the duration that the downstream firms become the main customers of the supplier. $\mathbf{X}_{i,t}$ is the time-varying information set for the supplier. $u_t$ denotes time-fixed effects. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.6

**Trade Credit Channel II-Weak Connections**

| | | | External Financial Dependence | | Liquidity Needs | |
|---|---|---|---|---|---|---|
| | Weak Connections | | High | Low | High | Low |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| wdummy_sc*MP | 0.40** | 0.41** | 0.69*** | 0.015 | 0.64** | 0.14 |
| | (0.15) | (0.16) | (0.25) | (0.19) | (0.27) | (0.17) |
| wdummy_sc | 0.54*** | 0.36 | 0.73** | 0.31 | 0.63** | 0.45** |
| | (0.16) | (0.22) | (0.25) | (0.20) | (0.26) | (0.19) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes |
| Supplier_Industry | Yes | No | Yes | Yes | Yes | Yes |
| Supplier | No | Yes | No | No | No | No |
| Observations | 9,335 | 9,335 | 4,629 | 4,726 | 4,285 | 5,070 |
| Supplier | 1,473 | 1,473 | 780 | 693 | 731 | 756 |
| $Adj-R^2$ | 0.04 | 0.12 | 0.05 | 0.04 | 0.05 | 0.04 |

**Note**: Statistical significance: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. The regression equation is: $Rech_{i,t}/sale_{i,t} = \alpha_0 + \alpha_1 * wdummy\_sc_{i,t} * MP_t + \alpha_2 * wdummy\_sc_{i,t} + \gamma * \mathbf{X}_{i,t} + u_i + u_t + \epsilon_{i,t}$. $Rech_{i,t}$ is changes in supplier $i$'s account receivables in year $t$. $sale_{i,t}$ denotes supplier $i$'s total sales. Here, in the last four columns, we use weak connection dummy in Table 3.3. The first two columns use all observations in our sample. In the median two columns, we divide the whole sample into two subsamples based on customers' industry-level trade credit dependence which corresponds to the ratio of account payable over total sales. In the last two columns, we divide the whole sample into two subsamples based on customers' industry-level liquid needs which is equal to the ratio of short-term debt over sales. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

Appendix A3.7

**Heterogeneous Effects**

| | Trust1 | | Trust2 | | Trust3 | |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| $wdummy\_sc * MP$ | 0.012 | 0.030*** | 0.011 | 0.031** | 0.021 | 0.020 |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| $wdummy\_sc$ | 0.051** | 0.043** | 0.051** | 0.042** | 0.015 | 0.078*** |
| | (0.021) | (0.019) | (0.021) | (0.020) | (0.018) | (0.022) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effect | | | | | | |
| Time | Yes | Yes | Yes | Yes | Yes | Yes |
| Pair | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,663 | 6,327 | 5,649 | 6,341 | 5,846 | 5,840 |
| Pairs | 1,152 | 1,227 | 1,153 | 1,226 | 1,149 | 1,151 |
| $Adj - R^2$ | 0.66 | 0.66 | 0.67 | 0.67 | 0.67 | 0.66 |

**Note**: Statistical significance: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.This table presents the results of the following empirical specification: $log(\frac{Sale_{i,j,t}}{Sale_{i,t}}) = \beta_0 + \beta_1 * wdummy\_sc_{i,j,t} * MP_t + \beta_2 * wdummy\_sc_{i,j,t} + \beta_3 * MP_t + \beta_4 * c_size_{j,t} + \gamma * \mathbf{X}_{i,t} + u_{i,j} + \epsilon_{i,j,t}$, where $Sale_{i,j,t}$ and $wdummy\_sc_{i,j,t}$ are the sales and the index of social connections between supplier $i$ and customer $j$ in year $t$ respectively. We use the dummy variable of social ties between upstream and down stream firms as the main index of social connections. This dummy equals to one if there exists at least one of the senior managers and board members from the supplier ever attended a same educational institution or worked at a same company with one of the corresponding customer's senior managers and board members (weak connections). $Sale_{i,t}$ is the total sales of supplier $i$ in period $t$. $MP_t$ is the index of monetary contractions in year $t$. $c\_size_{j,t}$ is the time-variant total assets of customer. In addition, we add suppliers' vector of controls (suppliers' size, profitability and asset tangibility) in the regression to check the robustness of our result. We control for pair-fixed effects, $u_{i,j}$ and time-fixed effect $u_t$. We divide the sample into two subsamples based on the state-level social trust. Here "Low" means that the suppliers are located in a state with low social trust while "High" means that the suppliers are in the state with high social trust. In the first two columns, "Trust1" denotes the social trust constructed from Sen. Mike Lee's Social Capital Project and "Trust2" represents the social trust constructed by Gallup in 2009. Heteroscedasticity robust standard errors clustered at the pair and year levels are reported in parentheses.

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# Curriculum Vitae

- Ph.D in Economics; University of Bonn (2014-2019)
- M.Sc in Economics; Hong Kong University of Science and Technology (2012-2013)
- B.A in Economics; Zhejiang University (2008-2012)