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by

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Abstract

This dissertation analyzes micro-level data and employs a general equilibrium model to study heterogeneous firm-level responses to aggregate shocks, underlying sources of the observed difference in firm's decisions, and industry and country-level implications.

The first chapter investigates how cross-sectional micro-uncertainty influences the investment of small and large firms and discusses the aggregate implications of the heterogeneity in their investment decisions. Empirically, we find that large firms show less investment decline in times of heightened uncertainty. We provide empirical evidence for the underlying driver of the observed size effect: the heterogeneous responses across firms are in fact the consequence of large firms operating in multiple markets rather than their size per se. To interpret these findings, we build a heterogeneous firm model with single- and multi-unit firms subject to (i) unit-level real frictions, i.e., fixed and convex investment adjustment costs and (ii) firm-level financial frictions, i.e., costly equity issuance. In the model with unit-level frictions, an increase in uncertainty lowers the investment of both single and multi-unit firms through a 'wait-and-see' effect. For a multi-unit firm, on the other hand, firm-level financial frictions generate the interdependence of investment across units within a firm, i.e., a fall in investment in one unit enlarges internal funds and so relaxes the constraint on the amount a firm can invest in the other unit. Therefore, upon uncertainty shocks, multi-unit firms lower their investment by less than single-unit firms. This is because the 'wait-and-see' effect is partially offset by the relaxation of financial constraints due to the availability of larger internal funds when investment in one unit decreases. To examine the aggregate implications due to the heterogeneity in firms' responses, we compare the benchmark economy to a counterfactual economy with only single-unit firms. The result shows that the contribution of multi-unit firms is sizable in alleviating the impact of uncertainty shocks on aggregate investment.

In the second chapter, with Korean firm-level and aggregated industry-level data, we uncover a balance sheet channel through which the exchange rate shock translates into domestic prices. Exploiting the quasi-natural experiment environment during the Asian Financial Crisis, we investigate how exposure to foreign currency debt prior to the crisis leads to different price dynamics. Our empirical finding suggests that when a sector had a higher level of short-term foreign currency debt ratio prior to the crisis, the price increase is more pronounced. Based on this empirical result, we build a heterogeneous firm model to study the transition path upon an unexpected real exchange rate shock, calibrated to match the real exchange rate changes in the 1996-98 period in Korea. In our model, a currency depreciation inflates the domestic value of foreign currency debt. As a consequence, firms, with a high share of their debt in foreign currency, face tighter working capital constraint and reduce their investment more, leading to higher costs of production and higher prices. The model is able to generate qualitatively consistent and quantitatively sizeable price increase upon a large depreciation of the currency, and furthermore, explain the cross-sectional variation in the sectoral price changes across industries. We also find that the interaction of strategic complementarity in firms' price settings and heterogeneity in foreign currency debt holdings across firms within an industry play an important role in amplifying the negative balance sheet effect on industry-level price dynamics.

Chapter 1

The Impact of Uncertainty Shocks on the investment of Small and Large Firms: Micro evidence and Macro Implications

1.1 Introduction

How uncertainty affects economic activities has been a long-lasting question and has recently drawn particular attention under the COVID-19 pandemic. The general consensus in the literature is that uncertainty has a negative impact on economic activities, especially investment. Rich evidence from existing studies shows the impact of uncertainty shocks on aggregate investment (Gilchrist et al. (2014), Bloom et al. (2018)) and the average impact on firm-level investment (Leahy and Whited (1995), Bloom et al. (2007)). However, the literature has not paid much attention to how the impact of uncertainty shocks is systematically different across firms and the underlying reasons for this difference. In this paper, we fill the gap in the literature by investigating how uncertainty influences the investment of small and large firms and discuss the aggregate implications. Firm size is one of the most essential firm-level characteristics because both small and large firms always coexist within an economy. At the same time, the distribution of small and large firms shows substantial differences across countries and times. Therefore, examining the differential impact of uncertainty shock is important because (i) it helps to understand the transmission mechanism of uncertainty to investment choice, and (ii) we can precisely evaluate the overall impact of uncertainty shocks on aggregate investment in a given country and at a given time.

The key questions in this paper are as follows: (i) Do small and large firms respond differently to an increase in uncertainty? (ii) If so, what is the potential source of the discrepancy? (iii) What is the macroeconomic consequence due to the heterogeneity in investment decisions? We address these questions in two steps. First, using micro firm-level data, we document empirical findings that small firms reduce their investment more than large firms in times of heightened uncertainty. We provide empirical evidence for the underlying mechanism of the observed size effect – the number of lines of business. Second, we build a heterogeneous firm model with single and multi-production unit firms to account for the findings and discuss the aggregate implications.

We start by conducting an empirical analysis using detailed U.S. firm-level Compustat data. This dataset allows us to investigate relatively high-frequency long-panel data, which helps to precisely estimate the size effect. Furthermore, rich balance-sheet information enables us to uncover the size effect. The uncertainty measure is based on the cross-sectional dispersion of the unexpected component of the industry-level output growth rate over the economy following Bloom et al. (2018). In the baseline analysis, we estimate how the semi-elasticity of investment with respect to uncertainty varies with firm size. We find that a firm whose size is one standard deviation larger than that of the average firm is one-third less responsive to uncertainty. This result is robust under various specifications. In particular, we control the interaction between size and another set of aggregate variables to alleviate the concern that the observed size effect merely reflects the excess cyclicality of small firms documented by Crouzet and Mehrotra (2020) due to the highly countercyclical nature of uncertainty.

Based on the previous finding, we proceed to uncover the observed size effect. We find that the heterogeneous responses across firms are in fact the consequence of large firms operating in multiple industries (lines of business) rather than their size per se. That is, once we control the number of lines of business, firm size loses its significance in explaining heterogeneous responses. However, the semi-elasticity of investment to uncertainty significantly depends on the number of lines of business such that a firm with one more line of business than the average firm is less responsive by 35%. We control another set of variables that might explain the size effect. In particular, a higher firm borrowing cost due to the increase in default risk is one of the important channels through which uncertainty has a real effect. Since large firms or firms operating in multiple markets tend to have a lower level of default probability, the size effect might reflect the default risk channel. In this regard, we control firm-level leverage and "distance to default", which are known to capture firm-level default risk (Ottonello and Winberry (2020)). However, we do not find any evidence that the observed size effect is associated with firm-level default probability or debt burden.

To interpret the empirical findings and discuss the aggregate implications, we build a standard general equilibrium heterogeneous firm model with two extensions. First, firms are allowed to choose the number of production units when they enter the market. The unit can be interpreted as a different line of business, a different factory, or a different geographical market as long as the unit needs its own production inputs and faces a certain degree of idiosyncratic shocks. Second, each firm faces two types of frictions. At the unit level, a firm has to incur fixed and convex adjustment costs upon non-zero investment. At the firm level, if a firm decides to raise funds from the external financial market, it has to pay a finance cost as in Gomes (2001). Due to firm-level financial frictions, the boundary of the firm has an important implication for firm-level investment behavior.

In the model, multi-unit firms are less responsive to uncertainty shocks, and most of the dampened effect is associated with the interaction between the real options channel and the inter-dependence of investment within a multi-unit firm. The inter-dependence arises from the real and financial frictions that cause a multi-unit firm to give up simultaneously investing in both units. Under this situation, even though a multi-unit firm has a good investment opportunity in one unit, it is sometimes willing not to invest because the other unit also has a good opportunity and internal funds are limited. Then, how does this interrelationship alleviate the impact of uncertainty shocks? An increase in uncertainty causes firms to initially pause their investment through the real options channel. At the same time, the initial reduction of investment in one unit enlarges internal funds and has a positive effect on the other unit's investments. Hence, the initial decrease in investment through the real options channel is partially offset by the positive effect of relaxing financial constraints. Obviously, multi-unit firm diversification also has a dampening effect, but we find that most differences are explained by the inter-dependence effect.

We calibrate the model to match the standard moments in the literature. The model generates the nontargeted moments from the empirical analysis reasonably well. Then, we study the aggregate implication of firm-level heterogeneity by contrasting the benchmark economy with the counterpart economy, which has only single-unit firms. The goal of this analysis is to investigate the contribution of a multi-unit firm's dampened response to aggregate investment fluctuation due to uncertainty shocks. We find that the presence of a multi-unit firm has an adverse effect on a single-unit firm's response because the general equilibrium-smoothing effect is less favorable to single-unit firms in the benchmark economy. However, overall, a multi-unit firm helps to mitigate the negative effect of uncertainty shocks on aggregate investment. This result arises from the fact that multi-unit firms account for a significant portion of the economy and the dampened effect of the multi-unit firm's response is large. This result suggests that the role of heterogeneity crucially depends on the adjustment of the market price, especially the real interest rate, and the distribution of firms.

The remainder of the paper is organized as follows: Section 2 provides information on the related literature. Section 3 provides micro empirical evidence. Section 4 describes the structural model to address the main question. Section 5 presents how we choose parameter values in the model. Section 6 studies the main underlying mechanism in the model and Section 7 explores the aggregate implications. Section 8 concludes.

1.2 Literature review

This paper contributes to three broad streams of literature. The first stream explores the role of uncertainty shocks over the business cycle. Several related works uncover the effect of uncertainty shocks using a structural general equilibrium model. Bachmann and Bayer (2013) and Bloom et al. (2018) show the macroeconomic implications of uncertainty shocks using a framework under real frictions, i.e., non-convex adjustment costs, in a frictionless financial market environment. Another set of papers focuses on the financial friction channel through which uncertainty shocks affect real variables. Arellano et al. (2019) explore the effect of volatility shocks on the labor market under an incomplete financial market with default risk. In a similar spirit, Gilchrist et al. (2014) emphasize the role of financial frictions due to default risk. Christiano et al. (2014) provide a relatively simple framework to explore the impact of volatility shocks on the agency problem. They show that a significant portion of business cycle fluctuations in the U.S. can be explained by volatility shocks. Unlike the papers listed above, Alfaro et al. (2018) argue that both real and financial frictions are important. They show that the interaction between these frictions indeed amplifies the effect of uncertainty shocks under partial equilibrium. Our model is closely related to Alfaro et al. (2018) in terms of the frictions imposed, but we investigate the general equilibrium implications and distinguish single and multi-unit firms. We contribute to the literature by showing that the effect of uncertainty shocks significantly relies on certain characteristics of firms, i.e., the number of production units, and the aggregate implications due to the firm's heterogeneous responses.

Second, this paper contributes to the literature on small and large firms' business cycle fluctuations. Ghosal and Ye (2015) and Ghosal and Loungani (2000) show that an industry that is more populated by small firms tends to respond more to uncertainty shocks in terms of investment and employment. Gertler and Gilchrist (1994) show that small firms respond more to monetary policy shocks than larger firms by focusing on the Romer-Romer episodes. Extending the dataset used by Gertler and Gilchrist (1994), Chari et al. (2007) argue that the average cyclical behavior of small firms is roughly the same as that of large firms in more general recession episodes other than the Romer-Romer dates. Based on the same dataset, Kudlyak and Sanchez (2017) show that large firms' short-term debt and sales contracted relatively more than those of small firms during the 2008 financial crisis. Recently, Crouzet and Mehrotra (2020) show that the top 1% of large firms are less cyclically sensitive than the bottom 99% of smaller firms and that the industry scope of the largest firms is associated with the size effect. We extend this literature by showing the differential impact of uncertainty shocks on small and large firms and by providing an underlying mechanism–empirically and theoretically–to explain the size effect.

Third, this paper contributes to the literature that studies the implications of firms' boundaries on investment decisions. Matvos and Seru (2014) show that resource allocation within diversified firms significantly alleviates the effect of external financial market disruption on investment choice. Giroud and Mueller (2015) show that shocks to one plant propagate to other plants within the same firm by reallocating capital and labor. They show that this interaction is significant only if the firm is financially constrained. Almeida et al. (2015) study capital allocation within Korean business groups (chaebol) in the aftermath of the 1997 Asian crisis. They show that chaebol reallocated the resources from firms with low-growth opportunity to those with high-growth opportunity, which helps to mitigate the effect of financial disruption. Kehrig and Vincent (2019) show that among multi-plant firms, most of the variation in the plant-level investment rate occurs within a firm rather than between firms. They argue that in the presence of real and financial frictions, dispersion within a firm results from optimizing behavior and will improve firm performance. We contribute to the literature by showing that the firm's boundaries also play an important role in determining the effect of uncertainty shocks on investment.

1.3 Empirical analysis

In this section, we address the following questions: (i) Are small firms more responsive to uncertainty than large firms? (ii) If so, what characteristics of small and large firms make the discrepancy? Detailed U.S. firm-level Compustat data are used to address the above questions. This dataset allows us to investigate high-frequency long-panel data, which help to precisely estimate the size effect. Furthermore, rich balance sheet data, which are merged with two other datasets, i.e., Compustat Segment and CRSP, enable us to distinguish the size effect from effects due to another dimension of heterogeneity.

Data description

Firm-level variables The main dependent variable is $\Delta \log k_{i,t+1}$, where $k_{i,t+1}$ is the book value of the tangible capital stock of firm i at the end of period t, which is deflated by the nonresidential fixed investment good deflator. We use the change in capital stock rather than investment rates based on capital expenditure because micro-level investment is known to be lumpy and erratic, which poses a challenge to precisely estimating the systematic differences in investment behavior across firms and times, as noted by Jeenas (2018). The log of real sales and real book value of total assets are used as proxies for firm size. Another set of variables capturing the firm-level characteristic consists of liquidity, the sales growth rate, current-assets-to-total-assets ratio, the sales-to-capital ratio, leverage, the distance to default, and the number of lines of business. The main firm-level characteristics other than firm size are leverage, the distance to default and the number of lines of business because they are potential candidates that might explain the observed size effects. The detailed reasons for the choice of these variables are described in the following section. Total debt to total asset ratio is used for the leverage measure. To calculate the distance to default, we merge Compustat with CRSP data and follow Bharath and Shumway (2008) for data processing. The information on the number of lines of business is drawn from Compustat Segment data and calculated following Decker et al. (2016).[1] The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors. The data are cleaned and constructed based on the standard practice in the investment literature, following Ottonello and Winberry (2020). Details on the data cleaning and construction process are available in the appendix.Table 1.1 presents the summary statistics of the main variables used in the empirical analysis.

[1]Since the Compustat Segment data contain only annual frequency information, the annual information on the lines of business is used to fill in the quarterly data within the same calendar year.

Table 1.1: Summary statistics

(i) Marginal Distributions

	size (sales)	size (total assets)	$\Delta \ln k$	lev	lob	dd
Mean	4.02	5.06	0.007	0.28	2.49	3.84
Median	4.17	5.48	0.0005	0.23	2	3.53
Std	2.5	2.45	0.13	0.38	1.58	4.0
Bottom 5%	-0.18	1.59	-0.08	0	1	-0.69
Top 5 %	7.9	9.56	0.12	0.73	6	10.06

(ii) Correlation matrix

	size (sales)	size (total assets)	lob	lev	dd
size (sales)	1.0				
size (total assets)	0.9324	1.0			
lob	0.3220	0.3178	1.0		
lev	-0.017	0.0483	0.0177	1.0	
dd	0.2168	0.2725	0.0758	-0.2200	1.0

Note: Size is the log of real sales or real book value of total assets, $\Delta \ln k$ is the log change in the capital stock, lev is the ratio of total debt to total assets, dd is the distance to default measure, and lob is the number of lines of business.

Panel (i) in Table 1.1 shows the marginal distribution of selected firm-level variables, and Panel (ii) shows the unconditional pairwise correlations. As we can see in Panel (ii), large firms tend to have more lines of business and a higher value of the distance to default, which justifies their use as potential sources of size effects. Furthermore, the distance to default is negatively correlated with a firm's leverage, which indicates that a higher debt burden implies a higher default risk.

Uncertainty The uncertainty measure is based on the cross-sectional dispersion of the unexpected component of industry-level output growth rate throughout the economy following Bloom et al. (2018). The main advantage of using this uncertainty measure over using firm-level volatility as a proxy for uncertainty, as in previous works, is that the former uncertainty measure can alleviate potential endogeneity issues because all firms in the economy face the same degree of uncertainty, which is orthogonal to the idiosyncratic firm-level endogenous components driving firm-level volatility shocks.[2] Furthermore, this choice of uncertainty is consistent with the uncertainty in the model. In the structural model, the firm is not identical to the production unit and can own different production units with different productivities. Additionally, the fluctuation of uncertainty is modeled as the time-varying cross-sectional dispersion of tomorrow's unit-level productivities. Since the lines of business that are identified by the industry (SIC 2-digit) in the empirical analysis correspond to the production units in the model, the uncertainty based on the cross-sectional dispersion of industry-level output growth is the most suitable choice.

We identify the uncertainty measure by estimating the following regression for each industry s

$$g^s_{t+1} = \alpha_s + \beta_s g^s_t + \gamma_s Z_t + u_{s,t+1}$$

where g^s_t is the industry s's output growth at time t; Z_t is the observable macro conditions, i.e., GDP growth, the effective federal funds rate, the unemployment rate, and the CPI inflation rate; and $u_{s,t+1}$ is the unforeseen components of the industry output growth rate. $u_{s,t+1}$ consists of common factor f_{t+1} and idiosyncratic factor $\epsilon_{s,t+1}$:

$$u_{s,t+1} = f_{t+1} + \epsilon_{s,t+1}.$$

Since the main focus is the cross-sectional dispersion of industry-specific unforeseen shocks $\epsilon_{s,t+1}$, to back them out, we run a simple panel regression with only time-fixed effects and sector-fixed effects to control not only the common factor but also permanent differences across sectors as follows

$$u_{s,t+1} = \alpha_t + \alpha_s + e_{s,t+1}.$$

Then, we use $e_{s,t+1}$ as an estimate for $\epsilon_{s,t+1}$, calculate the interquartile range of $e_{s,t+1}$ across sectors and use the result as an estimate of uncertainty at time t

$$\sigma_t = IQR_t(e_{s,t+1}).$$

[2]There might be a concern that each industry faces different level of uncertainty. We deal with this concern by controlling sector-by-time fixed effect.

Heterogeneous response to uncertainty

Baseline results The baseline regression is

$$\Delta \log k_{i,t+1} = \alpha_i + \alpha_{s,t} + \beta size_{i,t-1} \times Unc_t + \Gamma' Z_{i,t-1} + \epsilon_{i,t} \tag{1.1}$$

where α_i is a firm-level fixed effect, $\alpha_{s,t}$ is a sector-by-time fixed effect, and $Z_{i,t-1}$ consists of the lagged value of firm-level control variables, i.e., leverage, the distance to default, liquidity, the number of lines of business, sales growth, the current-assets-to-total-assets ratio, size, and the fiscal quarter. The log of real sales and real total assets are used as proxies for size. The lagged value of size and firm-level controls are used to alleviate potential endogeneity issues. The main coefficient of interest is β, which measures how the semi-elasticity of investment $\Delta \log k_{i,t+1}$ with respect to uncertainty depends on firm size. In the regression, both size measures are standardized over the entire sample. Hence, the increase in one unit of the size measure can be interpreted as one standard deviation of the size relative to the sample mean. Standard errors are clustered in two ways to account for correlation within firms and within quarters. Columns 1 and 2 in Table 1.2 show the results of the baseline regression. The coefficient estimate of the cross-product term is positive and statistically significant in both size measure specifications. Controlling the time by sector fixed effects, we can interpret that large firms reduce their investment less than smaller firms in times of heightened uncertainty. Since the results from different size measures give very similar results, we focus on sales in the following analysis.[3]

To investigate the average effect of uncertainty on a firm's investment, the sector-by-time fixed effect is omitted, and the following regression is estimated with uncertainty series and other sets of aggregate variables.

$$\Delta \log k_{i,t+1} = \alpha_i + \alpha_{s,q} + \gamma Unc_t + \beta size_{i,t-1} \times Unc_t + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_t + \epsilon_{i,t} \tag{1.2}$$

[3]The observed size effect might just reflect the excess cyclicality of small firms documented by Crouzet and Mehrotra (2020) due to the highly countercyclical nature of uncertainty. In the appendix, we perform extra exercises to control for the interaction of lagged size with the other aggregate variables to deal with the concern of the strong countercyclical nature of uncertainty.

Table 1.2: Results of the baseline regression

dependent variable: $\Delta \log k_{j,t+1}$

	1	2	3	4
size × uncertainty	0.29^{**}	0.28^{**}	0.25^{**}	0.29^{**}
	(0.13)	(0.14)	(0.11)	(0.13)
uncertainty			-0.77^{***}	-0.70^{***}
			(0.21)	(0.20)
time × sector fixed effect	yes	yes	no	no
obs	240,724	240,724	240,724	240,724
R^2	0.1127	0.1126	0.099	0.99
size measure	sales	total asset	sales	total asset

Notes: column 1 and 2 show the results from regression (1.1) and column 3 and 4 show the results from regression (1.2). Standard errors in parentheses are two-way clustered by firm and time. We standardize the size measure over the entire sample. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

where $\alpha_{s,q}$ is the sector-by-quarter fixed effects to control for seasonality and aggregate control variables Y_t consisting of the GDP growth rate, monetary policy rate, CPI-based inflation rate, and unemployment rate. Other control variables are the same as in the previous regression (1.1). Columns 3 and 4 in Table 1.2 report the regression results. Consistent with the existing literature as in Bloom (2009), the average impact of increase in uncertainty is estimated to be negative and statistically significant. The average investment semi-elasticity is -0.77 in response to a one-percentage-point increase in uncertainty. The cross-product term is still positive and statistically significant such that if the firm size is one standard deviation larger than that of the average firm, the investment semi-elasticity of the larger firm increases by 0.25, which is approximately one-third of the average firm's response.

Deciphering mechanism In the following analysis, we provide evidence for the underlying mechanism of the observed size effect. Based on the positive correlation between firm size and the number of lines of business, the following empirical analysis shows that the observed size effect is explained mostly by the number of lines of business. To rule out other possibilities, we also control the firm-level leverage ratio and distance to default measure. The choice of these controls is motivated by the theory in the literature–a higher firm borrowing cost due to an increase in default risk is an important channel through which uncertainty shocks affect real variables (Arellano et al. (2019), Gilchrist et al. (2014) and Christiano et al. (2014)). Since firm size is also highly correlated with the firm's default risk, as shown in Table 1.1, the observed size effect might represent the default risk channel. However, as is evident in the following regression analysis, the default channel does not seem to be successful in explaining the observed size effects. We provide further evidence that extensive margin adjustment plays an important role in explaining the differential responses, thus suggesting that the 'wait-and-see' effect is asymmetric across firms.

First, we run the following version of regressions to uncover the size effect:

$$\Delta \log k_{i,t+1} = \alpha_i + \alpha_{s,t} + \beta size_{i,t-1} \times Unc_t + \beta_\nu \nu_{i,t-1} \times Unc_t + \Gamma' Z_{i,t-1} + \epsilon_{i,t}. \quad (1.3)$$

The main difference between this version of the regression and the baseline regression (1.1) is the additional inclusion of the cross-product of uncertainty with a variable of interest, i.e., $\nu_{i,t-1}$, which is leverage (lev), the distance to default (dd) or the number of lines of business (lob). For each variable of interest, a different regression is performed with a different cross-product term. The leverage and the distance to default are chosen to capture the default risk as in Ottonello and Winberry (2020). As in Decker et al. (2016) and Matvos and Seru (2014), the number of lines of business (identified by two-digit SIC codes) can be interpreted as the number of production units each firm owns.

Table 1.3 shows the results. Column 1 repeats the results of the baseline regression (1.1) for ease of comparison. Columns 2 and 3 show the regression results when the leverage and the distance to default are controlled, respectively. However, their inclusion does not seem to change the coefficient estimate of the size effect

Table 1.3: Results of regression (1.3) - Deciphering mechanism

dependent variable: $\Delta \log k_{j,t+1}$

	1	2	3	4	5	6
size × unc	0.291**	0.278**	0.263**	0.144	0.091	0.112
	(0.130)	(0.131)	(0.129)	(0.110)	(0.109)	(0.109)
lev × unc		0.081			0.131	0.129
		(0.078)			(0.084)	(0.086)
dd × unc			0.155**		0.186**	-0.074
			(0.077)		(0.082)	(0.126)
lob × unc				0.253***	0.252***	0.256***
				(0.06)	(0.061)	(0.064)
unc						-0.71***
						(0.298)
time × sector fixed effect	Yes	Yes	Yes	Yes	Yes	No
obs	240,724	240,724	240,724	240,724	240,724	240,729
R^2	0.1127	0.1127	0.1127	0.1129	0.1130	0.0999

Notes: column 1 repeats the regression (1.1), column 2 includes leverage (lev), column 3 includes the distance to default (dd), column 4 includes the number of lines of business (lob) and column 5 includes all. In column 6, the time by sector fixed effect is dropped but quarter by sector fixed effects and several aggregate variables - GDP growth rate, monetary policy rate, CPI-based inflation rate, and unemployment rate - as well as uncertainty are controlled. Standard errors in parentheses are two-way clustered by firm and time. We standardize the size, leverage and the distance to default over the entire sample. For the number of lines of business, we subtract it by the average of the entire sample but do not divide it by the standard deviation. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

relative to the baseline results in Column 1. Column 4 shows the results with the number of firm production units. Compared to the default-level proxies, the number of production units significantly affects the coefficient estimate of the size effect. Column 5 includes all variables, and column 6 includes all variables but dropping sector and time fixed effects to examine the average effect of uncertainty, as in regression (1.2). The overall results suggest that the size effect is not driven mainly by the default-risk mechanism and that the number of production units has important implications for the observed size effect.

Ex-post behavior – ruling out the default risk channel Focusing on ex-ante firm-level heterogeneity would not be enough to rule out the possibility of the default-risk channel because there might be unobserved firm-level characteristics that covariate with firm size but cause the default risk of small firms to increase more than that of large firms. Alternatively, the number of production units would be a better proxy for a firm's default risk because if a firm owns more production units, it might be perceived as well diversified. In that case, a small firm's (stand-alone firm's) borrowing costs increase more, and hence, the small firm's (stand-alone firm's) investment drops more. To rule out this possibility, we investigate the ex-post change in default risks and financial variables. Similar to equation (1.2), except for the dependent variables, the following regression is performed:

$$\Delta y_{i,t} = \alpha_i + \alpha_{s,q} + \gamma Unc_t + \beta size_{i,t-1} \times Unc_t + \Gamma_1' Z_{i,t-1} + \Gamma_2' Y_t + \epsilon_{i,t}, \quad (1.4)$$

where $\Delta y_{i,t}$ equals three variables, namely, the change in the distance to default, the change in short-term debt, and the change in long-term debt.[4]

As we can see in Table 1.4, the coefficients on uncertainty are estimated to be statistically significant except those for the short-term debt, and all of them are estimated to be negative. Hence, uncertainty has a negative impact on all the dependent variables on average. However, the coefficient estimates on the cross-product between size and uncertainty turn out to be statistically insignificant in all cases. Furthermore, the signs of estimates are at odds with the idea that the size effect represents the default risk channel because negative coefficients imply that a large firm's default risk or financial variables respond more to uncertainty. We also include the interaction of the number of lines of business and uncertainty in Columns (3), (6), and (9), but the coefficients are not significantly different from zero. Overall, the findings in Table 1.4 seem inconsistent with the view that the observed size effect is driven mainly by the default risk channel.

[4] A change in the distance to default is normalized by its own lagged value, and changes in short-term and long-term debt are normalized by the lagged value of total assets.

Table 1.4: Results of regression (1.4) - Ex-post behavior

dep var	Δ dd			Δ short-term debt			Δ total debt		
	1	2	3	4	5	6	7	8	9
unc	-5.967*	-5.845*	-5.840*	-0.039	-0.036	-0.023	-0.172*	-0.166*	-0.194*
	(3.269)	(3.282)	(3.303)	(0.032)	(0.032)	(0.031)	(0.090)	(0.092)	(0.105)
size × unc		-0.654	-0.748		-0.019	-0.017		-0.035	-0.042
		(0.752)	(0.766)		(0.022)	(0.024)		(0.027)	(0.026)
lob × unc			0.091			-0.006			0.023
			(0.414)			(0.006)			(0.015)
obs	237,339	237,339	237,339	239,791	239,791	239,791	239,715	239,715	239,715
R^2	0.0357	0.0357	0.357	0.0263	0.0263	0.0263	0.0663	0.0663	0.0663

Notes: the dependent variable is (i) change of the distance to default in column 1 to 3, (ii) change of short-term debt in column 4 to 6 and (iii) change of total-debt in column 7 to 9. Standard errors in parentheses are two-way clustered by firm and time. We standardize the size over the entire sample. For the number of lines of business, we subtract it by the average of the entire sample but do not divide it by the standard deviation. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

Ex-post behavior – supporting the real options channel In the following analysis, we show additional evidence consistent with the idea that the observed size effect is closely related to the asymmetric 'wait-and-see' effect across different firms. Rather than relying on the default risk channel, a set of papers in the literature focuses on the real options mechanism through which uncertainty has a negative impact on a firm's investment via 'wait-and-see' effects (Bloom (2009), Bloom et al. (2018) and Bachmann and Bayer (2013)). That is, firms are more cautious about their investment in times of heightened uncertainty, so they postpone new investment projects until the uncertainty is resolved. This implies the extensive margin adjustment plays an important role in determining the firm's investment decision. Hence, if the real options channel drives the observed size effect, small and large firms must show different patterns in terms of an extensive margin as well as an intensive margin choice. The following version of the regression is performed to confirm the prediction:

$$\mathbf{I}(i_{j,t}/k_{j,t-1} > 0.05) = \alpha_i + \alpha_{s,t} + \beta size_{i,t-1} \times Unc_t + \beta_{LoB} LoB_{i,t-1} \times Unc_t + \Gamma' Z_{i,t-1} + \epsilon_{i,t} \tag{1.5}$$

where $i_{j,t}$ is the capital expenditures, $k_{j,t-1}$ is the lagged value of tangible capital, and the dependent variable $\mathbf{I}(i_{j,t}/k_{j,t-1} > 0.05)$ is the indicator variable, which takes a value of 1 if the firm's investment rate $i_{j,t}/k_{j,t-1}$ is larger than 5 percent or 0 otherwise. Here, we focus on large investment change, which is called investment spikes in the literature rather than inaction with zero investment because identifying inaction precisely at the micro level is a difficult task due to the substantial heterogeneity (i) in capital assets with associated heterogeneity in the depreciation rate and adjustment costs and (ii) in the types of investment episodes (e.g., maintenance vs. large new projects), as noted by Cooper and Haltiwanger (2006).[5]

Table 1.5 shows the results. Column 1 reports the results with the size effect. Consistent with the prediction of the real options channel, if firm size is one standard deviation larger than the average firm, the probability of investment spikes increases by 1.2 percent in times of heightened uncertainty. Column 2 reports the result with lines of business. If a firm owns one more line of business relative to the average number, the probability of investment spikes increases by 1.4 percent in response to increase in uncertainty. Column 3 shows the regression results when both the size and the number of lines of business are controlled. The inclusion of the number of lines of business significantly alters the coefficient estimate of the size effect, but that of lines of business is barely affected. Column 4 drops sector by time fixed effects to examine the average effect of uncertainty, as in regression (1.2). The average effect of uncertainty is estimated to be negative and statistically significant, and the effect is weaker for multi-unit firms. Therefore, the overall results suggest that the size effect reflects the real options channel rather than the default risk mechanism and that the real options effect is weaker for larger firms because they operate in

[5]The choice of a 5 percent threshold is standard in the literature (20 percent in the annual horizon). However, the result is not sensitive to thresholds from 3 to 15 percent.

Table 1.5: Results of regression (1.5) - Extensive margin adjustment

Dependent variable: $\mathbf{I}(i_{j,t}/k_{j,t-1} > 0.05)$

	1	2	3	4
size × uncertainty	1.204***		0.431	0.428
	(0.398)		(0.473)	(0.504)
lob × uncertainty		1.422***	1.335***	1.26***
		(0.323)	(0.370)	(0.371)
uncertainty				-1.63**
				(0.86)
time × sector fixed effect	yes	yes	yes	no
Observations	235,695	235,695	235,695	235,700
R^2	0.3404	0.3406	0.3406	0.3283

Notes: results from regression (1.5). column 1 includes size, column 2 includes the number of lines of business (lob) and column 3 includes all. In column 4, the time by sector fixed effect is dropped but quarter by sector fixed effects and several aggregate variables - GDP growth rate, monetary policy rate, CPI-based inflation rate, and unemployment rate - as well as uncertainty are controlled. Standard errors in parentheses are two-way clustered by firm and time. We standardize the size over the entire sample. For the number of lines of business, we subtract it by the average of the entire sample but do not divide it by the standard deviation. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

multiple production units. In the following section, we build up a structural model to explain the asymmetric real options effects on small and large firms based on the empirical findings.

1.4 Model

The model builds on Bachmann and Bayer (2013) and Bloom et al. (2018), who study the impact of uncertainty shocks based on the 'wait-and-see' mechanism under the general equilibrium framework. The economy consists of three types of agents: a representative household, single-unit firms, and multi-unit firms. The household consumes final goods, owns firms and supplies labor. Firms operate either single- or multi-production units. The units can be interpreted as different factories, different geographic markets, or different business segments or product lines within a firm as long as they need their own input for the production process and face a certain degree of idiosyncratic shocks, such as demand or productivity shocks. Firms are able to choose the number of units when they enter the market.[6] They hire labor to produce final goods and accumulate capital, which is subject to fixed and convex investment adjustment costs. The main departure of this model from the standard wait-and-see literature is a wedge between internal and external funds. In particular, when firms do not have enough funds to finance their investment project from their profit, they are able to issue new equity by paying finance costs, as in Gomes (2001). To focus on the friction between internal and external funds, we abstract from the distinction between debt and equity financing.

Firms

Physical environment The economy consists of a unit measure of firms that can choose the number of units to operate upon the entry. A multi-unit firm is assumed to own 2 different production units for numerical tractability. A large number of production units exponentially increases the computation burden due to the curse of dimensionality without adding any economic intuition.

For any given period, $\pi_N \in (0, 1)$ new firms enter the economy, and each firm draws a fixed cost γ from the distribution $F(\gamma)$. The random fixed cost γ follows i.i.d across firms and time. Given this cost, they decide whether to be multi-unit firms by paying it in the labor unit. Otherwise, the firm will be a single-unit firm without any cost. The initial state and optimization problem of entrants will be described below. To keep the measure of firms constant, it is assumed that each firm faces a fixed exit probability, π_N, that it will be forced to exit the market after

[6]Firms are not allowed to change the number of units once they choose. This assumption is based on the idea that firm's decision making on organizational structure is less relevant in the business cycle frequency (quarterly frequency in this paper). Futhermore, we investigate uncertainty shocks which show pretty transitory nature. In the appendix, we show that indeed, there is no systemetic relationship between uncertainty and firm's choice on the number of units in the data.

production in each period.

Each production unit is featured by Cobb-Douglas decreasing-returns-to-scale technology

$$y = Azk^{\alpha}n^{\nu}, \quad 0 < \alpha + \nu < 1,$$

where A is an aggregate TFP following the AR(1) process, which is common across all units in the economy:

$$\ln A' = \rho_A \ln A + \epsilon'_A, \quad \epsilon'_A \sim N(0, \sigma_A^2),$$

and z is a unit-level idiosyncratic productivity that also follows the AR(1) process for single-unit firms:

$$\ln z' = \rho_z \ln z + \epsilon'_z, \quad \epsilon'_z \sim N(0, \sigma_z^2),$$

and follows the VAR(1) process for multi-unit firms:

$$\begin{bmatrix} \ln z'_1 \\ \ln z'_2 \end{bmatrix} = \begin{bmatrix} \rho_z & 0 \\ 0 & \rho_z \end{bmatrix} \begin{bmatrix} \ln z_1 \\ \ln z_2 \end{bmatrix} + \begin{bmatrix} \epsilon'_1 \\ \epsilon'_2 \end{bmatrix}, \quad \begin{bmatrix} \epsilon'_1 \\ \epsilon'_2 \end{bmatrix} \sim N(0, \Sigma) \quad \Sigma = \begin{bmatrix} \sigma_z^2 & \sigma_{12} \\ \sigma_{12} & \sigma_z^2 \end{bmatrix}.$$

allowing nonzero correlation between different units within a multi-unit firm, which will reflect the firm-level shocks affecting both units within a firm. The standard deviation of future shocks σ_A and σ_z are known at the current period and are time-varying based on a two-state Markov chain.[7] The timing assumption reflects that firms become informed about the distribution of future shocks A' and z' that they will face. Thus, the evolution of σ_A and σ_z broadly captures the uncertainty of tomorrow's business conditions. k is the capital stock, and n is the labor hired for the production of output.

The beginning of the period distribution of single-unit firms over (z, k) is denoted by μ_S and that of multi-unit firms over (z_1, z_2, k_1, k_2) is denoted by μ_L. Therefore, the aggregate TFP A, the volatility of aggregate TFP σ_A, the volatility of unit-specific

[7] We assume that the correlation across different units within a firm is constant over time so that the covariance is also time-varying.

productivity shocks σ_z and the distributions μ_S and μ_L constitute the aggregate state $\mathbf{S} = \{A, \sigma_A, \sigma_z, \mu_S, \mu_L\}$.

Firms are subject to unit-level real frictions and firm-level financial frictions. Specifically, at the unit level, a firm has to incur fixed and convex adjustment costs upon non-zero investment. Formally,

$$\Phi(k, k') \equiv \frac{\phi_c}{2}\left(\frac{k' - (1-\delta)k}{k}\right)^2 k + \phi_f \mathbb{I}(k' \neq (1-\delta)k). \tag{1.6}$$

The fixed cost captures the disruptive effect of investment on the production process due to restructuring or installing new capital (Caballero et al. (1995), Cooper and Haltiwanger (2006), Doms et al. (1998), and Gourio and Kashyap (2007)). At the firm level, if a firm decides to raise funds from the external financial market via new equity issuance, it has to pay a finance cost as in Gomes (2001)

$$\psi(d; \mathbf{S}) = \begin{cases} \psi_1 + \psi_2(\mathbf{S}) \times \mid d \mid \quad \text{if} \quad d < 0 \\ 0 \quad \text{if} \quad d \geqslant 0 \end{cases} \tag{1.7}$$

Due to this extra cost, firms take external sources of funds as a last resource only when the sum of capital adjustment cost and investment exceeds the operating profit. This cost reflects expenditures for both direct costs associated with various information and disclosure requirements and other administrative expenses or indirect costs related to asymmetric information and managerial incentive problems. We also assume that the marginal finance cost $\psi_2(\mathbf{S})$ is a function of aggregate states, especially an increasing function of uncertainty following Alfaro et al. (2018). This assumption is motivated by (i) the predictions from the micro-founded model (Bigio (2015)), which show a negative relationship between uncertainty and financing costs based on adverse selection, and (ii) empirical evidence that uncertainty and external finance costs are highly positively correlated (Caldara et al. (2016)). All adjustment costs are in labor units and rebated to the representative household as a lump sum.

Single-unit firms At the beginning of the period, aggregate state $\mathbf{S}$ is realized, and a firm starts with predetermined capital stock k and idiosyncratic productivity z. Given the states, firms learn whether they exit after production with probability π_N or keep producing in the next period with probability $1-\pi_N$. Immediately thereafter, firms hire labor and produce output. If they survive, firms also choose the amount of dividend and investment under the frictions described in the previous section.

Let $V_0^S(z,k;\mathbf{S})$ be an expected value function of a firm just before it realizes whether it will exit or not. Then, it becomes

$$V_0^S(z,k;\mathbf{S}) = \pi_N \max_n\{Azk^\alpha n^\nu - w(\mathbf{S})n + (1-\delta)k - w(\mathbf{S})\Phi(k,0)\} + (1-\pi_N)V^S(z,k;\mathbf{S})$$

where $V^S(z,k;\mathbf{S})$ is the value function of surviving firms. If a firm does not continue, it chooses labor to maximize the current dividend to the representative household. Since it will not carry any capital stock into the future, i.e., $k' = 0$, the dividend of exiting firms consists of operating profits and the undepreciated capital stock minus the adjustment costs.

Surviving firms choose labor to maximize the current profit $Azk^\alpha n^\nu - w(\mathbf{S})n$. Furthermore, they choose the amount of investment to maximize the present value of dividends to the representative household. Upon nonzero investment, a firm has to pay adjustment costs in the labor unit. In addition, if the firm decides to increase the capital stock but the operating profits $Azk^\alpha n^\nu - wn$ are not sufficient to cover the firms' new investment $k' - (1-\delta)k > 0$ and physical adjustment costs $w\Phi(k,k')$, it raises external finance with finance costs. Due to the wedge between internal and external funds, it is never optimal to issue new equity while paying dividends, i.e., when the operating profits are sufficient to finance the investment project. To simplify the exposition, we define the firm's payout d before financing costs as

$$d = Azk^\alpha n^\nu - wn - k' + (1-\delta)k - w\Phi(k,k'),$$

If d is positive, a firm pays dividends to the household. A negative value of d implies that a firm does not have enough funds to finance its investment project so that it issues new equity. In the absence of financial distortions, the equity issuance $d < 0$ reduces the value of existing shares by the same amount. However, in the model with finance costs, the value of existing shares is reduced by more than the amount of newly issued shares.

Given an aggregate state $\mathbf{S}$, an individual state (z, k), and law of motions for the joint distributions μ_S and μ_L,

$$\mu_S' = \Gamma_S(\mathbf{S}), \quad \mu_L' = \Gamma_L(\mathbf{S}),$$

a surviving single-unitl firm maximizes the present value of d, net of financing costs $\psi(d; \mathbf{S})$ by solving the following Bellman equation

$$V^S(z, k; \mathbf{S}) = \max_{d,n,k'} \ d - w(\mathbf{S})\psi(d; \mathbf{S}) + E\left[m(\mathbf{S}, \mathbf{S}')V_0^S(z', k'; \mathbf{S}') \mid z; \mathbf{S}\right]$$

where

$$d = Azk^{\alpha}n^{\nu} - w(\mathbf{S})n - k' + (1-\delta)k - w(\mathbf{S})\Phi(k, k'), \tag{1.8}$$

$\Phi(k, k')$ is defined by (1.6), finance cost $\psi(d; \mathbf{S})$ is defined by (1.7), $m(\mathbf{S}, \mathbf{S}')$ is the stochastic discount factor, and $V_0^S(z', k'; \mathbf{S}')$ is the expected value function just before firms realize exit status.[8]

Multi-unit firms The timing of a multi-unit firm is the same as that of a single-unit firm. At the beginning of the period, aggregate state $\mathbf{S}$ is realized, and a firm starts with capital stock k_1, k_2 and idiosyncratic productivity z_1, z_2 in each unit. Given the states, firms learn whether they exit or not. Immediately thereafter, they hire labor and produce output. Firms who realize they survive choose the investment to maximize the precent value of dividends to the household.

Let $V_0^L(z_1, z_2, k_1, k_2; \mathbf{S})$ be an expected value function of a multi-unit firm just

[8]Since all firms are owned by the representative household, the discount factor is $m(\mathbf{S}, \mathbf{S}') = \beta u_c(\mathbf{S}')/u_c(\mathbf{S})$, where β is the time discount factor, $u_c(\mathbf{S}')$ and $u_c(\mathbf{S})$ are the marginal utility of consumption for current and next period, respectively.

before it realizes whether it will exit or not. Then, it becomes

$$V_0^L(z_1, z_2, k_1, k_2; \mathbf{S}) = \pi_N \max_{n_1, n_2}\{Az_1k_1^{\alpha}n_1^{\nu} + Az_2k_2^{\alpha}n_2^{\nu} - w(\mathbf{S})(n_1+n_2) + (1-\delta)(k_1+k_2)$$

$$-w(\mathbf{S})(\Phi(k_1, 0) + \Phi(k_2, 0))\} + (1-\pi_N)V^L(z_1, z_2, k_1, k_2; \mathbf{S})$$

where $V^L(z_1, z_2, k_1, k_2; \mathbf{S})$ is the value function of surviving multi-unit firms.

At the unit-level, a multi-unit firm faces the same friction as single-unit firms, i.e., fixed and convex adjustment costs of physical capital. However, due to the firm-level financial frictions, larger boundary of a multi-unit firm plays an important role in determining investment and financing decisions. Specifically, a multi-unit firm can reallocate resources across different units without any frictions. If it does not have enough cash flows generated by unit 1 to finance investment project in the same unit, e.g., $Azk_1^{\alpha}n_1^{\nu} - wn_1 < k_1' - (1-\delta)k_1 + w\Phi(k_1, k_1')$, the firm can reallocate the profit from the other unit to avoid finance costs. On the other hand, if a firm has good investment opportunities in both units, it compares two different scenarios – (i) investing in one unit which gives higher return without relying on the external finance or (ii) investing in both units by raising funds from costly equity issuance – and chooses more profitable one. Hence, the way in which a multi-unit firm is affected by firm-level finance costs is different from that of a single-unit firm.

A surviving firm maximizes the present value of d, net of financing costs $\psi(d; \mathbf{S})$. Given an aggregate state $\mathbf{S}$, an individual state (z_1, z_2, k_1, k_2), and law of motions for the joint distributions

$$\mu_S' = \Gamma_S(\mathbf{S}), \quad \mu_L' = \Gamma_L(\mathbf{S}),$$

a multi-unit firm solves the following Bellman equation by choosing d, n_1, n_2, k_1', k_2'

$$V^L(z_1, z_2, k_1, k_2; \mathbf{S}) = \max_{d, n_1, n_2, k_1', k_2'} d - w\psi(d; \mathbf{S}) + E\left[m(\mathbf{S}, \mathbf{S}')V_0^L(z_1', z_2', k_1', k_2'; S') \mid z_1, z_2; \mathbf{S}\right]$$

where

$$d = Az_1k_1^{\alpha}n_1^{\gamma} + Az_2k_2^{\alpha}n_2^{\gamma} - w(\mathbf{S})(n_1 + n_2) - (k_1' + k_2') + (1-\delta)(k_1 + k_2) \quad (1.9)$$

$$-w(\mathbf{S})\big(\Phi(k_1, k_1') + \Phi(k_2, k_2')\big)$$

and $V_0^L(z_1', z_2', k_1', k_2'; \mathbf{S}')$ is the expected value function immediately before firms realize exit status.

Entrants Each new firm starts with zero capital stock but is able to issue new equity to finance the investment. Entrants are subject to the capital adjustment cost and finance cost. A single-unit firm will draw the idiosyncratic productivity shock z from an ergodic distribution $G_1(z)$ implied by the AR(1) process of the idiosyncratic productivity shocks to incumbent firms. Given the same aggregate conditions and law of motions for distributions as incumbent firms, the single-unit firm solves

$$V_E^S(z; \mathbf{S}) = \max_{k', d}\ d - w(\mathbf{S})\psi(d; \mathbf{S}) + E\Big[m(\mathbf{S}, \mathbf{S}')V_0^S(z', k'; \mathbf{S}') \mid z, \mathbf{S}\Big]$$

where $d = -k' - w\phi_f$ and the finance cost $\psi(d; \mathbf{S})$ is defined by (1.7).[9]

If a firm chooses to be a double-unit firm, it will draw two distinct idiosyncratic productivity shocks z_1 and z_2 from the ergodic distribution $G_2(z_1, z_2)$, which is implied by the VAR(1) process for incumbent firms. Then, the double-unit firm solves

$$V_E^L(z_1, z_2; \mathbf{S}) = \max_{k_1', k_2', d}\ d - w(\mathbf{S})\psi(d; \mathbf{S}) + E\Big[m(\mathbf{S}, \mathbf{S}')V_0^L(z_1', z_2', k_1', k_2'; \mathbf{S}') \mid z_1, z_2; \mathbf{S}\Big]$$

where $d = -k_1' - k_2' - 2w\phi_f$ and the finance cost $\psi(d; \mathbf{S})$ is defined by (1.7) subject to the same aggregate conditions and law of motions for distributions as incumbent firms.

[9]Since new entrants start with zero capital stock, their convex adjustment cost is assumed to be zero.

Given the value functions of new firms, the measure of firms who choose to be multi-unit will be determined. Specifically, define the threshold level of fixed cost $\hat{\gamma}(\mathbf{S})$ as

$$w(\mathbf{S})\hat{\gamma}(\mathbf{S}) \equiv \int V_E^L(z_1, z_2; \mathbf{S}) dG_2(z_1, z_2) - \int V_E^S(z; \mathbf{S}) dG_1(z).$$

New firms with fixed cost $\gamma < \hat{\gamma}(\mathbf{S})$ will choose to be multi-unit firms since

$$\int V_E^L(z_1, z_2; \mathbf{S}) dG_2(z_1, z_2) - \int V_E^S(z; \mathbf{S}) dG_1(z) > w(\mathbf{S})\gamma,$$

i.e., the benefit of being a multi-unit firm is larger than the cost. Therefore, the measure of new firms who choose to operate in multiple unit becomes $\Pr(\gamma < \hat{\gamma}(\mathbf{S})) = F(\hat{\gamma}(\mathbf{S}))$.

Household

There is a representative household that chooses the consumption, labor supply, and investment in firm shares to maximize lifetime utility.

$$U(s; \mathbf{S}) = \max_{C, N, s'(z,k), s'(z_1, z_2, k_1, k_2)} \ln C - \theta N + \beta E\big[U(s'; \mathbf{S}') \mid \mathbf{S}\big], \quad \theta > 0$$

given the following budget constraint

$$C + (1 - \pi_N)\bigg(\int s' p_s \; d\mu_S(z, k) + \int s' p_s \; d\mu_L(z_1, z_2, k_1, k_2)\bigg)$$

$$+ \pi_N\bigg(\int s' p_{s,new} \; dG_1(z) + \int s' p_{s,new} \; dG_2(z_1, z_2)\bigg)$$

$$= w(\mathbf{S})N + (1 - \pi_N)\bigg(\int s(\tilde{d} + p_s) \; d\mu_S(z, k) + \int s(\tilde{d} + p_s) \; d\mu_L(z_1, z_2, k_1, k_2)\bigg)$$

$$+\pi_N\bigg(\int s \; \tilde{d}_{Exit} \; d\mu_S(z, k) + \int s \; \tilde{d}_{Exit} \; d\mu_L(z_1, z_2, k_1, k_2)\bigg) + Adj_0(\mathbf{S})$$

where $w(\mathbf{S})$ is the wage, $Adj_0(\mathbf{S})$ is the income from the adjustment cost by firms, which includes both physical and financial adjustment costs, p_s is the value of stock, s is the share of previous period equity and s' is the share of equity chosen today. For simplicity, the arguments of $\tilde{d}$, $\tilde{d}_{Exit}, p_s, p_{s,new}, s, s'$ are suppressed (those variables are functions of $(z, k; S)$ or $(z_1, z_2, k_1, k_2; S))$. $\tilde{d}$ is either the dividend payment or effective equity issuance of surviving firms. When $\tilde{d}$ is positive, the household earns dividend payments from the firm so that $\tilde{d} = d$, where d is the firm's payout before finance costs are defined as (1.8) and (1.9). However, if $\tilde{d}$ is negative, there is zero dividend to the household. In this case, $\tilde{d} = d - w\psi(d; \mathbf{S}) < 0$ represents the new equity issuance plus the issuance cost, which is the gap between the current value of total equity and that of pre-existing equity. $p_{s,new}$ is the value of new firms, and $\tilde{d}_{Exit}$ is the dividend payments from exiting firms.

Recursive equilibrium

A recursive competitive equilibrium in this economy is defined by a set of
(i) quantity functions: $\{C, N, s', K'_S, N^d_S, K'_{1,L}, K'_{2,L}, N^d_{1,L}, N^d_{2,L}, K^E_S, K^E_{1,L}, K^E_{2,L}\}$,
(ii) pricing function: $\{w, p_s, p_{s,new}, m\}$,
(iii) lifetime utility and value functions: $\{U, V^S_0, V^L_0, V^S_E, V^L_E\}$,
where $\{V^S_0, V^L_0\}$ and $\{K'_S, N^d_S, K'_{1,L}, N^d_{1,L}, , K'_{2,L}, N^d_{2,L}\}$ are the value and policy functions of incumbent single- and multi-unit firms, respectively, and $\{V^S_E, V^L_E\}$ and $\{K^E_S, K^E_{1,L}, K^E_{2,L}\}$ are the value and policy functions of newborn single- and multi-unit firms, while U and $\{C, N^S, s'\}$ are the value and policy functions that solve the household problem.

Given the quantity and pricing functions, the goods market clears with

$$C(S) = \int Azk^{\alpha} N^d_S(z, k; \mathbf{S})^{\nu} \; d\mu_S(z, k)$$

$$+ \int \sum_{i=1,2} Az_i k_i^{\alpha} N^d_{i,L}(z_1, z_2, k_1, k_2; \mathbf{S})^{\nu} \; d\mu_L(z_1, z_2, k_1, k_2)$$

$$-(1-\pi_N)\int (K'_S(z,k;\mathbf{S})-(1-\delta)k)\ d\mu_S(z,k)$$

$$-(1-\pi_N)\int \sum_{i=1,2}(K'_{i,L}(z_1,z_2,k_1,k_2;\mathbf{S})-(1-\delta)k_i)d\mu_L(z_1,z_2,k_1,k_2)$$

$$+\pi_N\left[\int (1-\delta)k\ d\mu_S(z,k)+\sum_{i=1,2}(1-\delta)k_i\ d\mu_L(z_1,z_2,k_1,k_2)\right]$$

$$-\pi_N\left[\int_{\gamma>\gamma(\hat{\mathbf{S}})}\int K^E_S(z,0;\mathbf{S})dG_1(z)dF(\gamma)+\right.$$

$$\left.\int_{\gamma<\gamma(\hat{\mathbf{S}})}\int \sum_{i=1,2}K^E_{i,L}(z_1,z_2,0,0;\mathbf{S})dG_2(z_1,z_2)dF(\gamma)\right],$$

the labor market clears with

$$N(S)=\int N^d_S(z,k;\mathbf{S})d\mu_S(z,k)+\int\left[\sum_{i=1,2}N^d_{i,L}(z_1,z_2,k_1,k_2;\mathbf{S})\right]d\mu_L(z_1,z_2,k_1,k_2).$$

$$+\int \text{Adj Cost}_S(z,k;\mathbf{S})d\mu_S(z,k)$$

$$+\int \text{Adj Cost}_L(z_1,z_2,k_1,k_2;\mathbf{S})d\mu_L(z_1,z_2,k_1,k_2)+\int_{\gamma<\hat{\gamma}(\mathbf{S})}\gamma dF(\gamma)$$

and the asset market clears with

$$s'(z,k;\mathbf{S})=1,\ \forall\ (z,k)\quad s'(z_1,z_2,k_1,k_2;\mathbf{S})=1\ \forall\ (z_1,z_2,k_1,k_2).$$

Lastly, the evolution of the joint distributions over (k,z) and (k_1,k_2,z_1,z_2) are consistent. That is,

$$\mu'_S=\Gamma_S(\mathbf{S})\quad\text{and}\quad\mu'_L=\Gamma_L(\mathbf{S})$$

are generated by the policy functions $\{K'_S,K'_{1,L},K'_{2,L},K^E_S,K^E_{1,L},K^E_{2,L}\}$ and the exogenous stochastic evolution of $\{A,z,(z_1,z_2),\sigma_A,\sigma_z\}$.

1.5 Calibration

Fixed parameters Table 1.6 shows the parameters taken from the literature. The model period is a quarter, which corresponds to the empirical analysis. The discount factor is $\beta = 0.99$, the depreciation rate is $\delta = 0.03$ and the labor disutility parameter is $\theta = 2$, which are standard in the literature. Following Winberry (2020), we set the capital share $\alpha = 0.21$ and the labor share $\nu = 0.64$, which implies the total return as 85%. Following Koby and Wolf (2020), we assume 6.5 % of annual exit rates so that 1.625 % of firms exit at a quarterly frequency. For the parameters regarding exogenous shocks on productivities and uncertainty, we borrow from Bloom et al. (2018) who estimate the shock processes using establishment-level data. Because the uncertainty shocks are modeled as an increase in the standard deviation of unit-level productivity shocks, their measure of shock processes is the most suitable for this analysis. Following their approach, we assume that a single underlying process σ governs the evolution of both micro σ_z and macro σ_A uncertainties so that

$$\sigma = L \quad \Rightarrow \quad \sigma_A = \sigma_{A,L} \text{ and } \sigma_z = \sigma_{z,L}, \quad \sigma = H \quad \Rightarrow \quad \sigma_A = \sigma_{A,H} \text{ and } \sigma_z = \sigma_{z,H}$$

and σ follows a two-state Markov process with the following transition probability:

$$\Pi = \begin{bmatrix} \pi_{L,L} & \pi_{L,H} \\ \pi_{H,L} & \pi_{H,H} \end{bmatrix} \quad \text{where} \quad \pi_{L,L} + \pi_{L,H} = \pi_{H,L} + \pi_{H,H} = 1.$$

Finally, we assume that the marginal cost component of financing cost $\psi_2(\mathbf{S})$ is an increasing function of σ as in Alfaro et al. (2018). Specifically,

$$\psi_2(\sigma) = \begin{cases} \psi_2 & \text{if} \quad \sigma = L \\ 1.38 \times \psi_2 & \text{if} \quad \sigma = H \end{cases} \tag{1.10}$$

implying the finance cost under high uncertainty is 1.38 times higher than that under low uncertainty.[10]

Table 1.6: List of fixed parameters

Parameter	Description	Value	Data Source
β	Time discount factor	0.99	Standard
θ	Labor Disutility	2	Standard
δ	Depreciation rate (Physical Capital)	0.03	Standard
α	Capital Share	0.21	Winberry (2020)
ν	Labor Share	0.64	Winberry (2020))
π_N	Measure of New Firms (Exit prob)	0.01625	Koby and Wolf (2020)
ρ_z	AR coeff of z	0.95	Bloom et al. (2018)
ρ_A	AR coeff of A	0.95	Bloom et al. (2018)
$\sigma_{z,L}$	STD of z (Low)	0.051	Bloom et al. (2018)
$\sigma_{A,L}$	STD of A (Low)	0.0067	Bloom et al. (2018)
$\sigma_{z,H}$	STD of z (High)	$4.1 \times \sigma_{z,L}$	Bloom et al. (2018)
$\sigma_{A,H}$	STD of A (High)	$1.6 \times \sigma_{A,L}$	Bloom et al. (2018)
$\pi_{L,H}$	Transition prob from Low to High	0.026	Bloom et al. (2018)
$\pi_{H,H}$	Transition prob from High to High	0.943	Bloom et al. (2018)
$\psi_2(H)$	Marginal finance cost (High)	$1.38 \times \psi_2$	Alfaro et al. (2018)

Fitted parameters The key parameters in the model are the adjustment costs. In particular, the degree to which the investment of a multi-unit firm is different from that of a single-unit firm crucially depends on the relative magnitude between the physical capital adjustment cost and financial adjustment costs. If physical capital adjustment costs outweigh financial costs, unit-level friction dominates a firm's investment behavior so that single- and multi-unit firms will show little difference. On the other hand, the high value of finance costs makes the boundary of the firm more important so that the investment behavior of multi-unit firms will be significantly different from that of single-unit firms. Therefore, precisely estimating the adjustment costs places a discipline on the degree of difference between single- and multi-unit firms' investment behavior. The correlation between units within a multi-unit firm is also important to determine the gap between single- and multi-unit

[10] ψ_2 is the marginal finance cost under low uncertainty and is the fitted parameter.

firms because more diversified multi-unit firms are less responsive to uncertainty shocks. Therefore, we calibrate all fixed-adjustment costs regarding unit-level and firm-level frictions and the correlation across units within a multi-unit firm by matching the following cross-sectional empirical moments in the next section.[11]

Table 1.7: List of fitted parameters

Parameter	**Description**	**Value**
$\bar{\gamma}$	Upper Bound for Distribution of γ	4.03
$\sigma_{1,2}$	Corr bw z_1 and z_2 within a firm	0.2845
ϕ_F	Fixed adjustment cost (Physical Capital)	0.042
ϕ_C	Convex adjustment cost (Physical Capital)	0.217
ψ_1	Finance cost (Fixed)	0.001
ψ_2	Finance cost (Proportion)	0.18

Targeted moments We mainly target moments of establishment-level investment rates in Census micro data reported by Cooper and Haltiwanger (2006) and Kehrig and Vincent (2019) Table 1.8 shows the targeted moments. None of the values are taken from Compustat – but in the following section, we compare the moments from the model to the results from the empirical analysis. Even though we do not target any moments from the empirical analysis, the model successfully captures the data pattern. The first four moments in Table 1.8 are known to be informative for adjustment costs in the literature (Cooper and Haltiwanger (2006) and Winberry (2020)). As illustrated by Koby and Wolf (2020), whether firm-level heterogeneity has important implications for aggregate investment dynamics crucially depends on the degree of semi-elasticity of investment to the interest rate. Large elasticity implies that a firm's investment is highly sensitive to interest rate changes so that the general equilibrium smoothing effect from real interest rate adjustment will

[11]Consistent with the data moments, we consider only surviving firms in the model. To calculate the cross-sectional moments, we shut down all aggregate shocks, derive a stationary equilibrium, simulate 5000 firms and collect the simulated data at the production-unit level. Since all targeted moments are annual frequency, we aggregate the data from the model up to the yearly horizon when we calculate the moments.

be strong enough to offset the initial large drop of a single-unit firm's investment. In that case, firm-level heterogeneity will have limited implications for aggregate investment dynamics. Hence, we target semi-elasticity to precisely evaluate the importance of firm-level heterogeneity for aggregate investment.

Table 1.8: Targeted moments (annual)

Target	**Data**	**Model**
Average Investment Rate (%)	12.2%	16.1%
Standard Deviation of Investment Rates (%)	33.7%	37.5 %
Spike Rate (%)	18.6%	19.0 %
Serial Correlation of Investment Rate	0.058	0.14
Elasticity to real interest rate shock	5.0	5.34
Variance Share of i/k within Multi-Unit Firms (%)	66.3%	62.0 %
Multi-Unit Firm's Output Share (%)	78%	77.3 %

To precisely calibrate the relative magnitude between physical investment adjustment costs and financial adjustment costs, we target the share of variance in the investment rate accounted for by variation within a multi-unit firm. Kehrig and Vincent (2019) find that among the total variance of establishment-level investment rate, 66.3% is explained by the within-firm variation. They show that a large variance in the investment rate within a multi-unit firm arises when firms tend to invest large amounts into a few production units. This pattern of a multi-unit firm's staggered investment largely depends on the relative magnitude of investment adjustment cost and finance cost. If the investment adjustment cost is too high, whenever a firm decides to make a new investment, it would need extra funds. In this case, the incentive to focus the investment on one unit would be weaker. On the other hand, if the financial friction is severe and the investment adjustment cost is not too high, a firm would want to invest in one particular unit at a given time. Therefore, we target the variance share within a multi-unit firm to precisely estimate the adjustment costs.[12] Finally, the multi-unit firm's output share is informative for the upper bound of random fixed cost $\bar{\gamma}$ to be a multi-unit firm upon entry.

Calibration results Table 1.7 lists the fitted parameters and the calibrated results. The correlation across units within a multi-firm is calibrated as 0.2845, which implies that approximately one-third of unit-level productivity variance arises from firm-level shocks. The fixed adjustment costs of physical capital (0.042) and finance costs (0.18) are broadly consistent with the existing study by Alfaro et al. (2018), who estimate both fixed adjustment costs (0.036) and proportional finance costs (0.1435) using firm-level data. The convex adjustment cost is lower than that in existing studies, e.g., 0.7 in Koby and Wolf (2020), because the finance costs have a smoothing effect on the multi-unit firm's investment.

Model-induced regression results We compare the model with the empirical findings by running the same regression with the model-generated firm panel, which is simulated after we solve the general equilibrium with the calibrated parameters. We consider the fact that Compustat contains only publicly listed firms, whose median time of IPO is approximately 7 years (Wilmer and Pickering (2017)). Hence, we select firms that have survived for at least 7 years after being born. Table 1.9 shows the results. The coefficient estimate of the size and uncertainty interaction is 0.11 and that of the number of production units and uncertainty interaction is

[12] We calculate the variance share within a firm as follows. The total variance of i/k across production units, denoted by V_T, can be decomposed into two components:

$$\sum_j \omega_j \sum_{n=1}^{N_j} \frac{1}{N_j}\left[\left(\frac{i}{k}\right)_{n,j} - \left(\frac{i}{k}\right)\right]^2 \equiv V_T = \underbrace{\sum_j \omega_j \left[\left(\frac{i}{k}\right)_j - \left(\frac{i}{k}\right)\right]^2}_{V_B} + \underbrace{\sum_j \omega_j \sum_{n=1}^{N_j} \frac{1}{N_j}\left[\left(\frac{i}{k}\right)_{n,j} - \left(\frac{i}{k}\right)_j\right]^2}_{V_W}$$

where $\left(\frac{i}{k}\right)_j$ is the mean investment rate within-firm j, $\left(\frac{i}{k}\right)$ is the mean investment rate across all units, N_j is the number of units within firm j, and ω_j is the weight of firm j. The first term V_B is the variance between firms, and the second term V_W represents the average variance across units within a firm. Then, the variance share of i/k within a multi-unit firm is calculated as V_W/V_T.

Table 1.9: Results for empirical data vs. model data

Dependent variable: $\Delta \log k_{j,t+1}$

	Empirical			Model		
	1	2	3	4	5	6
Size × Uncertainty	0.29**		0.13	0.11		0.044
	(0.13)		(0.12)			
Number of units × Uncertainty		0.28***	0.25***		0.13	0.11
		(0.07)	(0.06)			
R^2	0.1126	0.1128	0.1128	0.1830	0.1828	0.1834

(Standard errors in parentheses are two-way clustered by firm and quarter. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.)

0.13, which are roughly less than half of the data counterparts. Furthermore, once we control both interaction terms, the size effect decreases by more than half in magnitude, but the coefficient estimate of the number of production units is not as affected as the size effect, which is consistent with the empirical patterns.[13]

1.6 Inspecting the mechanism

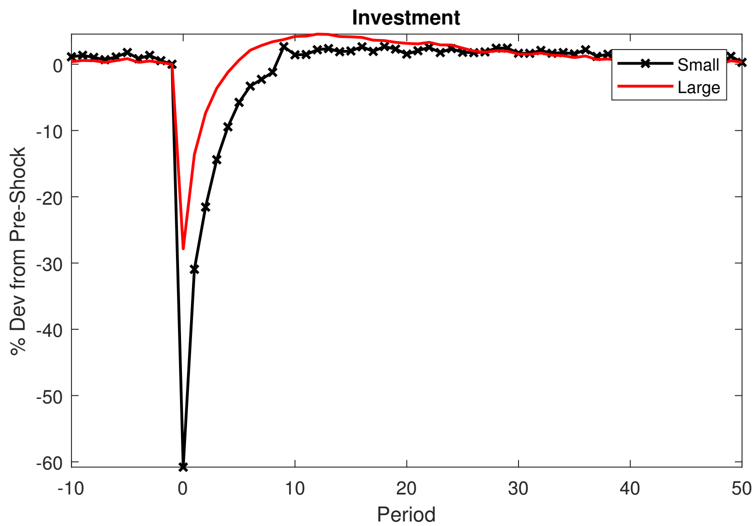
This section explores the underlying mechanism of firm-level decisions before proceeding to general equilibrium analysis. To precisely understand how uncertainty shocks affect a firm's investment choice, we fix all prices at the stationary equilibrium level and investigate only the incumbent firm's investment responses.[14] All parameter values are based on the previous section. We first provide different versions of the impulse responses and then investigate a firm's investment policy function.

Impulse responses Figure 1.1 plots the impulse responses of investment to uncertainty shocks among single and multi-unit firms, given the prices. To calculate

[13]We do not report standard errors for model-generated data because the number of obervation in the simulation is not comparable to the data counterpart.

[14]To calculate the stationary equilibrium, we shut down all the aggregate exogenous shocks, i.e. $A = 1$, $\sigma = \sigma_L$.

Figure 1.1: Impulse response functions under the partial equilibrium (1)



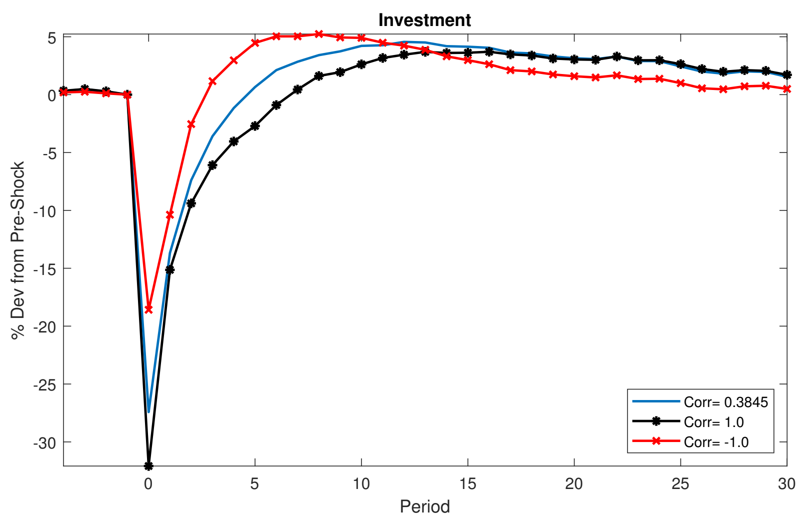
the impulse responses, we simulate 2000 independent economies with 100 quarters. Starting from the stationary equilibrium without any aggregate shocks, all exogenous shocks to aggregate TFP and uncertainty evolve normally according to the stochastic processes described in the previous sections before period 45. At period 45, we artificially impose a high level of uncertainty. After the shock period, the exogenous processes evolve normally again from period 46.[15] Upon the shock, all types of firms reduce their investments but to different extents, which successfully captures the differential impact of uncertainty shocks. Specifically, the single-unit firms reduce their investment by 61 %, which is approximately more than twice as large as the multi-unit firm's response of 29 %.

A natural way to explain this finding is the diversification benefit of multi-unit firms because idiosyncratic shocks are production-unit-specific and multi-unit firms can diversify the shocks as long as they are not perfectly correlated. However, the diversification proved not to be the sole factor driving heterogeneous responses. Figure 1.2 compares several investment responses of multi-unit firms with different levels of correlation across units. Clearly, as the correlation becomes negative,

[15] In the graph, period 0 corresponds to the shock period of 45.

i.e., the shocks are more diversified, the impact of uncertainty shocks is more alleviated. However, even in the case of perfect correlation, which is the case of no-diversification benefit, the response of a multi-unit firm's investment is 32 %, which is still more muted than that of a single unit firm's response of 61 %. This result implies that a significant factor other than diversification distinguishes the multi-unit firm's investment response.

Figure 1.2: Impulse response functions under the partial equilibrium (2)

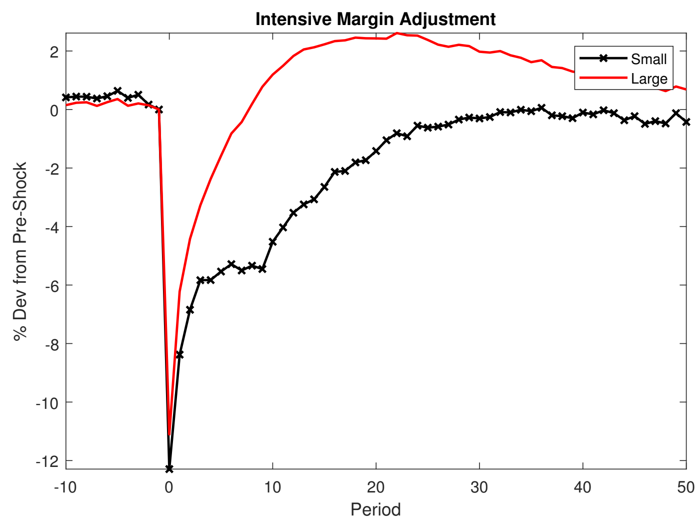


Note: this graph shows impulse response functions of multi-unit firms under different correlation structure.

To better understand the mechanism, we decompose the investment response into intensive and extensive margins and identify which margin plays an important role in explaining the differences. Figure 1.3 shows the investment response due to the intensive margin adjustment. We calculate the investment responses conditional on firms adjusting capital stocks, which is normalized by the measure of adjusting firms.[16] Once we consider only intensive margin adjustment, the gap between single and multi-unit firms becomes smaller than the gap of total investment responses. Specifically, the investment of single-unit firms decreases by 12% on impact, and

[16]We decompose the total investment responses as follows. For the single-unit firms, the total

Figure 1.3: Intensive vs. Extensive margin adjustments



that of multi-unit firms declines by 11 % due to the intensive margin, which shows little difference. This result implies that the gap between single and multi-unit firm

investment at $t+j$ among them is calculated as

$$I_{t+j} = \int i_{i+j}(z,k) d\mu_{S,t+j}(z,k).$$

Then, the log change of total investment from time t to $t+j$ can be decomposed as

$$\ln I_{t+j} - \ln I_t = \ln \int i_{i+j}(z,k) d\mu_{S,t+j}(z,k) - \ln \int i_i(z,k) d\mu_{S,t}(z,k)$$

$$= \ln \int i_{i+j}(z,k) d\mu_{S,t+j}(z,k \mid \text{adjust}) \pi_{S,t+j}(\text{adjust}) - \ln \int i_i(z,k) d\mu_{S,t}(z,k \mid \text{adjust}) \pi_{S,t}(\text{adjust})$$

$$= \underbrace{\ln \int i_{i+j}(z,k) d\mu_{S,t+j}(z,k \mid \text{adjust}) - \ln \int i_i(z,k) d\mu_{S,t}(z,k \mid \text{adjust})}_{\text{Intensive margin adjustment}}$$

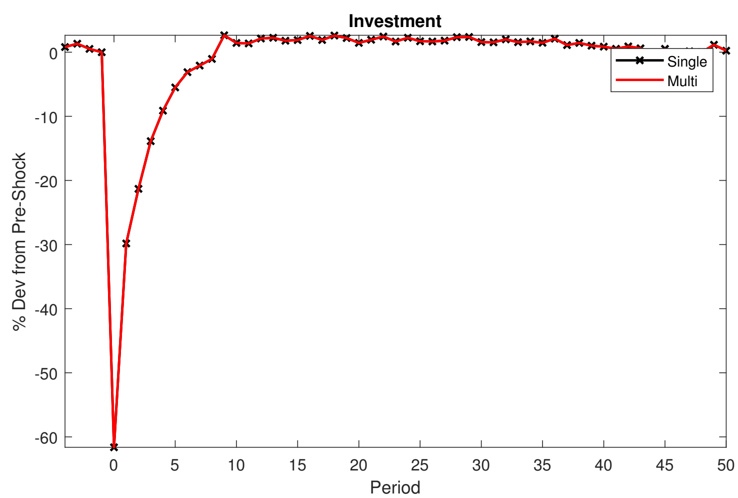
$$+ \underbrace{\ln \pi_{S,t+j}(\text{adjust}) - \ln \pi_{S,t}(\text{adjust})}_{\text{Extensive margin adjustment}}.$$

where $i_t(z,k)$ is the investment of firm (z,k) at time t, $\mu_{S,t}$ is the distribution of single-unit firms at time t, and $\pi_{S,t}(\text{adjust})$ is the measure of single-unit firms who adjust their investment at time t. For the multi-unit firms, we do this in a similar manner.

responses is driven mainly by the differential sensitivity of extensive margins to uncertainty shocks.

What feature of a multi-unit firm makes the extensive margin less responsive? Unlike a single-unit firm, a multi-unit firm is able to engage in within-firm resource allocation. That is, if a firm does not have enough profit generated by unit 1 to cover expenditure on investment in unit 1, the firm can use the profit from unit 2 without relying on the external finance market. Since utilizing internal capital markets is not available to the firms operating in a single production unit, it is one of the important characteristics of multi-unit firms. In Figure 1.4, we provide

Figure 1.4: Impulse response functions under the partial equilibrium (3)



Note: For the multi-unit firms, we shut down the internal resource allocation mechanism by assuming that the finance cost is unit-specific rather than firm-specific.

evidence that within-firm resource allocation is the key factor that distinguishes the differential response of single- and multi-unit firms. Figure 1.4 shows the impulse responses similar to the ones in Figure 1.1. The only difference from Figure 1.1 is that multi-unit firms are not allowed to pool the cash flows from two different units without any costs. That is, rather than assuming the firm-level financial friction, we assume that financial friction is unit-specific when we calculate the impulse response of multi-unit firms in Figure 1.4.[17] We further assume that the correlation between shocks to different units is -1, i.e., shocks are perfectly diversified. As we can see in Figure 1.4, the single- and multi-unit firms' responses are exactly the same despite the perfect diversification.[18] That is, once we eliminate the within-firm allocation mechanism, the difference between single- and multi-unit firms completely disappears. This result illustrates that the dampened investment response of a multi-unit firm crucially relies on the firm's ability to utilize internal capital markets. The following analysis examines the detailed mechanism by investigating each firm's investment policy function.

Policy functions Figure 1.5 illustrates the investment policy functions of single- and multi-unit firms under the median level of aggregate TFP and low uncertainty. To be specific, we compare the total investment of two single-unit firms and the total investment of one multi-unit firm under the same states. To simplify the analysis, we consider only the symmetric cases: two single-unit firms that have the same level of capital stock k and productivity z, and one multi-unit firm that has the same level of capital stock k and productivity z in each unit. Hence, the bottom panel in Figure 1.5 plots the sum of investment by two single-unit firms against initial capital stock k in one firm, and the top panel plots the total investment of a multi-unit firm against initial capital stock k in one unit. We fix the idiosyncratic productivities

[17] In this case, a multi-unit firm solves the following problem.

$$V^L(z_1, z_2, k_1, k_2; \mathbf{S}) = \max_{d_1, d_2, n_1, n_2, k_1', k_2'} d_1 + d_2 - w\psi(d_1; \mathbf{S}) - w\psi(d_2; \mathbf{S})$$

$$+E\left[m(\mathbf{S}, \mathbf{S}')V_0^L(z_1', z_2', k_1', k_2'; S') \mid z_1, z_2; \mathbf{S}\right]$$

where

$$d_1 = Az_1 k_1^{\alpha} n_1^{\gamma} - w(\mathbf{S})n_1 - k_1' + (1-\delta)k_1 - w(\mathbf{S})\Phi(k_1, k_1')$$
$$d_2 = Az_2 k_2^{\alpha} n_2^{\gamma} - w(\mathbf{S})n_2 - k_2' + (1-\delta)k_2 - w(\mathbf{S})\Phi(k_2, k_2')$$

[18] We try different levels of correlation (zero and perfect correlation), but the results are exactly the same. Since all firms are owned by a single representative household, whether an individual firm is diversified or not is not important from the household's perspective.

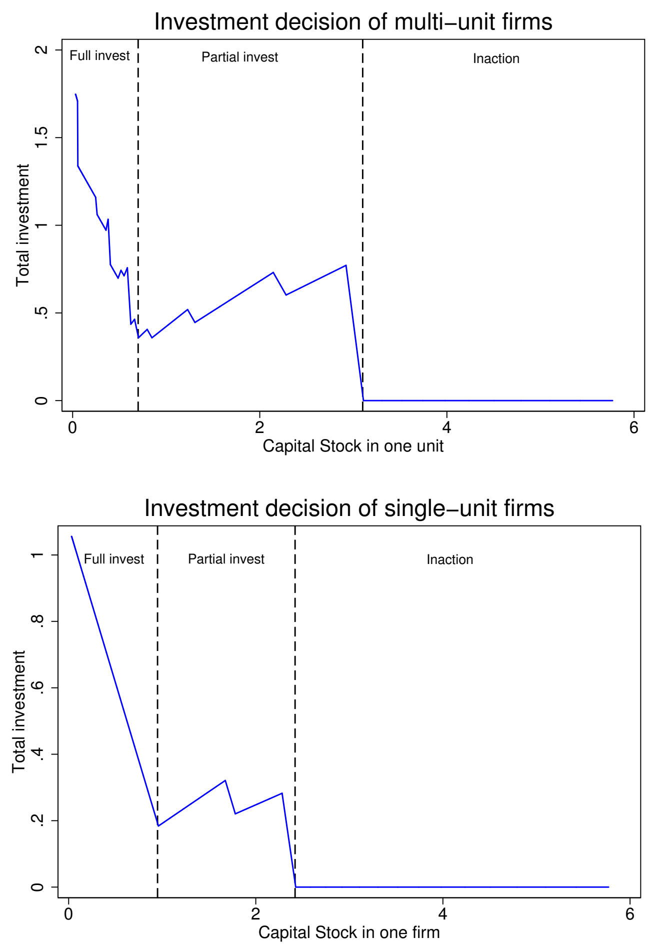
at the highest level and focus on the firm's positive investment decision in this analysis.[19] Furthermore, in order to investigate the pure 'wait-and-see' effect and rule out the diversification benefit, we assume zero convex capital adjustment cost and the perfect correlation between units within a multi-unit firm.

As we can see in Figure 1.5, both single- and multi-unit firms show qualitatively similar investment patterns. There is one region with zero investment (inaction region) and the other region with positive investment (investment region). The investment region is further decomposed into two distinct parts – one in which firms do not rely on external finance (partial investment region) and the other in which firms raise new equity for their expenditure on investment (full investment region). In the partial investment region, the presence of financial friction prevents firms from investing the full amount because the cost of using external finance is greater than the benefit. Hence, the firms optimally choose the constrained amount of investment that can be financed by internal funds.

Despite the qualitative similarity, the policy functions of single- and multi-unit firms show quantitative differences mainly due to the multi-unit firm's ability to engage in internal resource reallocation. First, the investment region of multi-unit firms is wider than that of single-unit firms. The situation arises when there is a good investment opportunity in one particular unit, but expenditure on the investment cannot be financed by the sole cash flow from the same unit. In this case, a multi-unit firm can use the profit from the other unit to cover the expenditure, but a single-unit firm would give up the opportunity because it does not have such an option and the investment opportunity is insufficient to compensate for costly external finance. Second, single-unit firms rely more than multi-unit firms on external finance, i.e., the full investment region of a single-unit firm is wider than that of a multi-unit firm. One interesting finding that is not seen in Figure 1.5 is that under the partial investment region, a multi-unit firm invests in one particular unit rather than in both units. This result is caused by the two different frictions –

[19] This analysis does not cover disinvestment decisions because (i) single- and multi-unit firms do not show any differences in disinvestment behavior, and (ii) a measure of firms who indeed reduce their investment is very small in my calibrated model due to the depreciation of physical capital.

Figure 1.5: Policy functions under low uncertainty

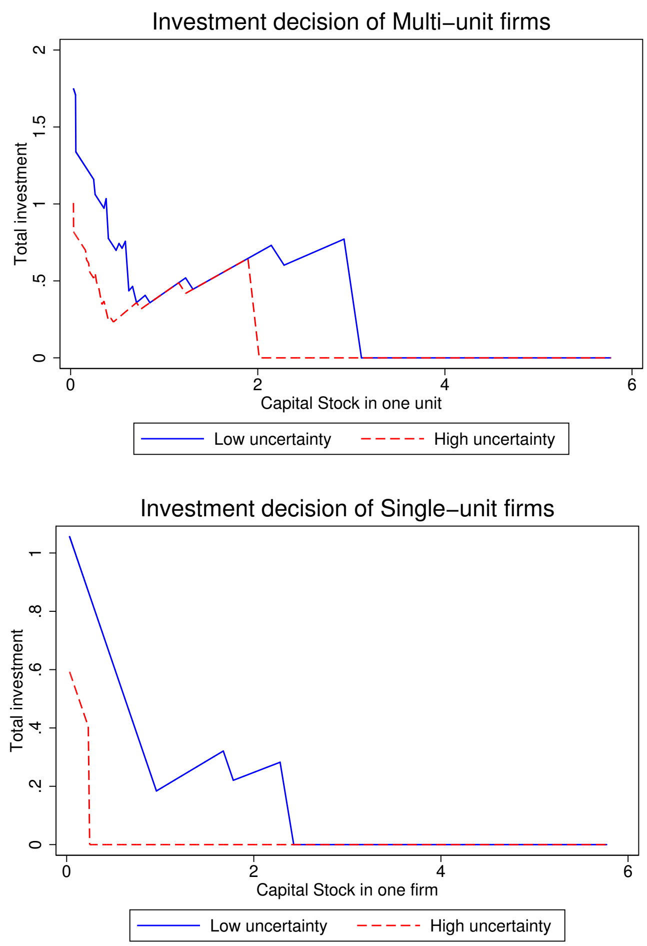


Note: Total investment of one multi-unit firm (top) and two single-unit firms (bottom) under low uncertainty. We only consider the symmetric case where a multi-unit firm has the same level of capital stock in each unit $k_1 = k_2 = k$ and two single-unit firms have the same level of capital stock k. Horizontal axis in top panel represents the level of capital stock in one unit, and that in bottom panel represents the level of capital stock in one firm. We fix the productivity at the highest value and the aggregate TFP at the median level.

(i) unit-level investment fixed cost and (ii) firm-level finance cost. In the presence of finance costs, a multi-unit firm tends to utilize internal funds for investment and tries to avoid allocating a large amount of new capital to both units within the same period. At the same time, due to the fixed investment adjustment cost, the small amount of investment is not profitable. As a result, the firm gives up investing simultaneously in both units and focuses its investment on one particular unit even though both units give exactly the same investment return. This pattern implies that the firm's investment decision for one unit crucially depends on the investment choice of the other unit, i.e., there is inter-dependence of investment within a multi-unit firm.

Figure 1.6 shows an exercise to investigate the effect of an increase in uncertainty. As in Figure 1.5, solid blue lines denote the policy functions under low uncertainty, and red dashed lines denote the policy functions under high uncertainty. As the top and bottom panels show, an increase in uncertainty enlarges the inaction regions of all types of firms through a 'wait-and-see' effect, but the effect is especially weaker for multi-unit firms. Similar to single-unit firms, multi-unit firms want to pause their investment when uncertainty is higher. However, for a multi-unit firm, the decision to postpone one particular investment project enlarges internal funds and so helps to relax the constraint on the amount a firm can invest in the other unit. Therefore, rather than delaying all the investment projects within its boundary, a multi-unit firm optimally chooses to delay one of its investment opportunities due to the 'wait-and-see' effect, but at the same time, the firm chooses to keep positive investment in the other unit because there are more internal funds available. That is, the multi-unit firm's dampened response arises mainly from the inter-dependence of investment within a firm. The top panel in Figure 1.6 illustrates the mechanism – a significant portion of multi-unit firms that planned to invest in both units (those in full investment region) under low uncertainty decide to invest in one unit under high uncertainty. Clearly, this mechanism is unavailable to a single-unit firm because it has one investment opportunity in its boundary. Hence, single-unit firms have no choice but to delay their investment. This prediction is confirmed in the bottom panel in Figure 1.6 – most single-unit firms that planned to invest (especially those in full investment region) under low uncertainty decide not to invest under high uncertainty. Therefore, the response of single-unit firms is larger than that of multi-unit firms.

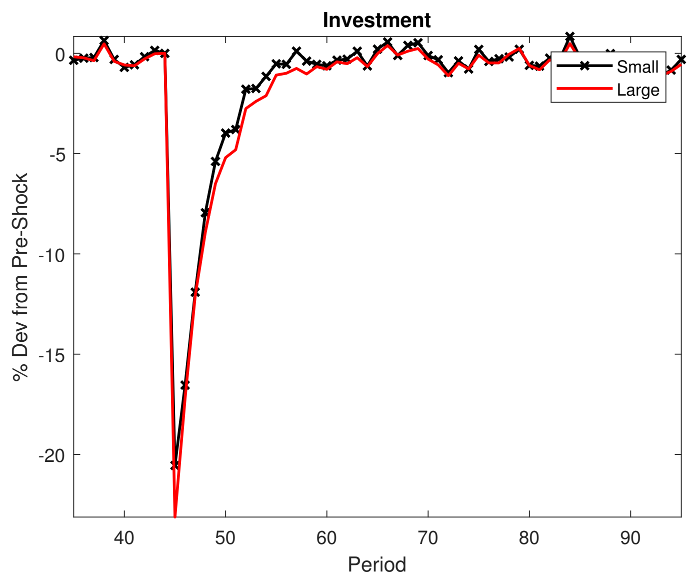
Figure 1.6: Policy functions under high uncertainty



Note: Total investment of one multi-unit firm (top) and two single-unit firms (bottom) under low uncertainty (blue solid line) and high uncertainty (red dashed line). We only consider the symmetric case where a multi-unit firm has the same level of capital stock in each unit $k_1 = k_2 = k$ and two single-unit firms have the same level of capital stock k. Horizontal axis in top panel represents the level of capital stock in one unit, and that in bottom panel represents the level of capital stock in one firm. We fix the productivity at the highest value and the aggregate TFP at the median level.

The different investment responses between single- and multi-unit firms crucially rely on the nature of shocks. Since the increase in uncertainty is modeled as a rise in the variance of next period productivities, a multi-unit firm decides to

Figure 1.7: Impulse response functions to negative aggregate TFP shock



Note: Aggregate TFP decreases 2% from the median value and shock occurs at period 45.

postpone its investment choice in both units initially without having a direct effect on the resources (profits) available to the firm. Therefore, the initial investment freeze in each unit could have offsetting effects because there are still enough funds available for the firm's investment project. In this regard, the first moment shock, i.e., a negative TFP shock, would have different implications because it directly affects the funds available to the firm. Figure 1.7 plots the impulse responses of investment to the negative TFP shock among single and multi-unit firms given the prices. In response to this shock, a multi-unit firm reduces its investment slightly more than a single-unit firm does. Therefore, the mechanism explaining the dampened effect of uncertainty shocks does not work and has the opposite prediction in the case of adverse TFP shocks.

Supportive evidence for the mechanism in the literature The main mechanism that distinguishes a multi-unit firm's investment behavior is driven by the negative interdependence of investment within a firm. The negative relationship would be more pronounced if firm-level financial friction were more severe because it arises from real and financial frictions. Kehrig and Vincent (2019) provide empirical evidence that the negative investment relationship within a multi-unit firm is indeed stronger in financially constrained firms, i.e., if multi-unit firms are more financially constrained, they tend to rotate the investment across plants rather than invest in both plants. In terms of a firm's alternating investment behavior, Becker et al. (2006) show that the fraction of zero investment and that of investment spikes are significantly lower at the firm level than at the plant level. They argue that those patterns suggest that firms smooth their investment but also concentrate on specific plants within a firm.

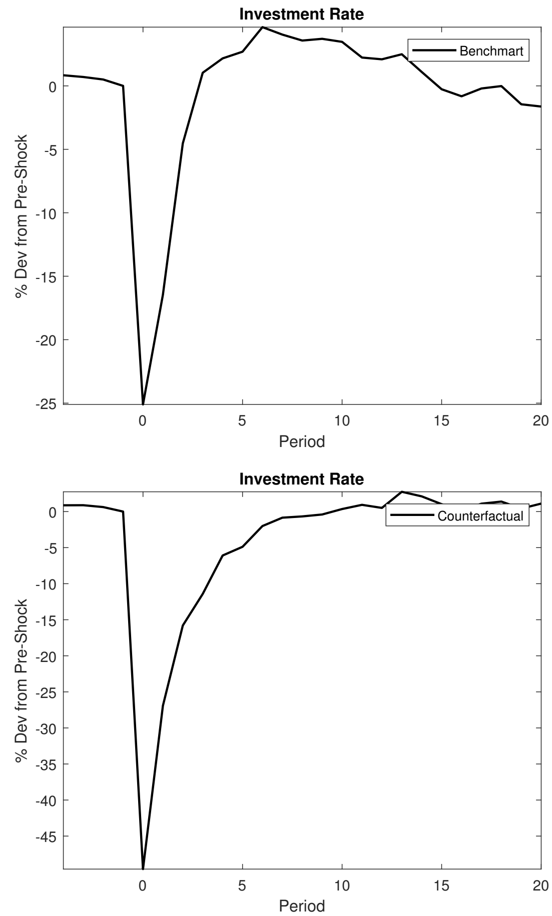
1.7 Aggregate implications

This section explores the aggregate implications of the heterogeneity in firms' investment decisions. Specifically, we examine how much the multi-unit firm's dampened responses contribute to alleviating the impact of uncertainty shocks on aggregate investment responses. To answer this question, we compare the aggregate investment response of the benchmark economy to that of a counterfactual economy with only single-unit firms. Both economies share the same parameters calibrated in the previous section. Since the infinite-dimensional distributions are state variables of individual firms, our model solution heavily relies on the numerical method by Krusell and Smith (1998). Details on the computation method is available in the appendix.

After we find the equilibrium, we calculate the impulse responses by simulating 2000 independent economies with 100 quarters. Each economy starts with the low uncertainty and median value of aggregate TFP. All exogenous processes evolve normally before period 45. At period 45, we artificially increase the level of uncertainty. After the shock period, the exogenous processes evolve normally again from period 46.[20]

[20]In the graph, period 0 corresponds to the shock period 45.

Figure 1.8: Impulse response functions under the general equilibrium (1)

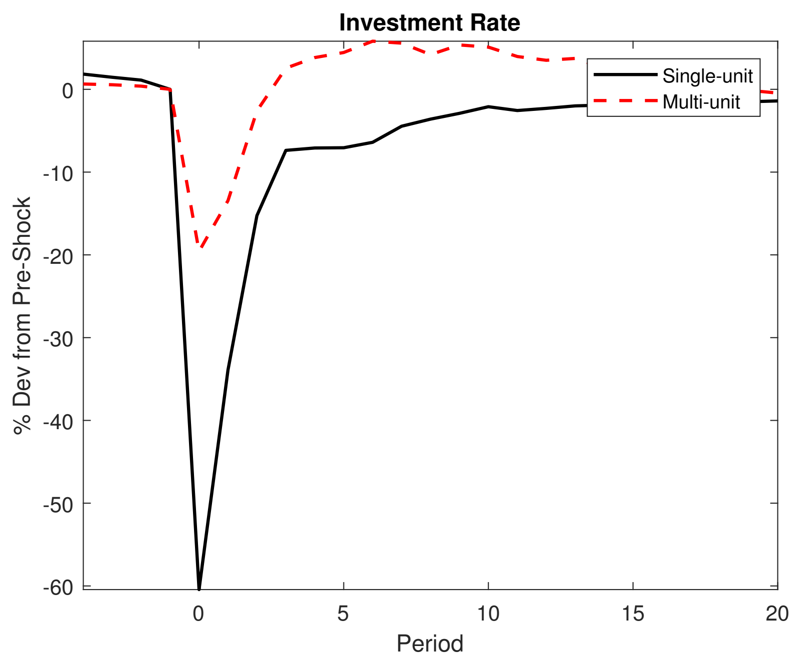


Note: this graph shows IRFs of investment to uncertainty shocks from the benchmark economy (left) and the counterfactual economy (right)

Figure 1.8 shows the response of aggregate investment to uncertainty shocks in the benchmark economy in the left panel, and the right panel shows the response in the counterfactual panel. In response to uncertainty shocks, investments in both economies decline, but the magnitude of the effect is much smaller for the benchmark economy. Furthermore, the benchmark economy shows quicker recovery than the counterpart economy, which is mainly because of multi-unit firms. Overall, the dampened response of multi-unit firms helps to mitigate the impact of uncertainty shocks significantly.

Figure 1.9 shows the responses of single- and multi-unit firm investment upon uncertainty shocks to the benchmark economy. Similar to the partial equilibrium responses, we find that the impact of uncertainty shocks is asymmetric across firms. Multi-unit firms reduce their investment by approximately 20 %, but single-unit firms reduce it by 60%, a response three times greater than the former.

Figure 1.9: Impulse response functions under the general equilibrium (2)



Note: this graph shows IRFs of investment to uncertainty shocks among single- vs. multi-unit firms under benchmark economy

An interesting finding is that in our benchmark economy, single-unit firms reduce their investment by 60% but in the counterfactual economy, single-unit firms reduce by 50%. That is, even though the aggregate investment responds less to the uncertainty, the single-unit firms indeed reduce their investment more in the benchmark economy. This result arises from the fact that, in the counterfactual economy, the general equilibrium smoothing effect is stronger. Since the initial decrease in investment is larger than that in the benchmark economy, the consumption tomorrow will decrease more, which leads to a larger decrease in the real interest rate. Since the real interest rate is the market price representing the cost of the investment, the price adjustment is more favorable to single-unit firms in the counterfactual economy such that the response of the single-unit firm itself is smaller. This result illustrates that the presence of a multi-unit firm makes the single-unit firm's response even worse. However, since the multi-unit firms account for a significant portion of the aggregate output and investment (78% of output in our benchmark economy) and the gap between single- and multi-unit firms' responses is sizable, the benefit from multi-unit firms is dominant. This finding suggests that the implication of firm-level heterogeneity on the aggregate investment response crucially relies on the general equilibrium adjustment effect and the distribution of firms.

1.8 Conclusion

In this paper, we show the asymmetric effect of uncertainty shocks on the investment of small and large firms. We argue that the observed size effect arises from the fact that large firms operate in multiple production units but small firms operate in a single unit. This argument is based on two components. First, we empirically show that the observed size effect is explained mostly by the number of business units of a firm. Second, we employ a heterogeneous firm model to account for the empirical results. In the presence of unit-level real and firm-level financial frictions, a multi-unit firm shows the negative interdependence of investment within a firm, which dampens the real options effect due to uncertainty shocks. We find that in equilibrium, the presence of multi-unit firms has an adverse effect on a single-unit firm's investment response. However, the dampened effect of uncertainty shocks to multi-unit firms still has important implications for aggregate investment responses because (i) multi-unit firms account for a significant portion of aggregate investment and (ii) the gap between single- and multi-unit firms' responses is sizable under general equilibrium.

Chapter 2

Liability Dollarization and Exchange Rate Passthrough [1]

2.1 Introduction

"Fear of floating" is pervasive in emerging economies. Many policymakers are concerned about volatile exchange rates, which forms some degree of aversion to completely floating their exchange rates, as once famously documented by Calvo and Reinhart (2002).

One immediate reason behind this epidemic anxiety is the exchange rate pass through to domestic prices. Price stability is the first and foremost important objective of the central banks, if not the only one. Therefore, volatile exchange rates can provoke an immense concern among central bankers as it may pass through to domestic prices, undermining their efforts to create a low inflation environment. Naturally, many researchers, therefore, have devoted their studies on how large exchange rate fluctuations may work as cost shocks to firms, and thus affect their prices of goods sold in the domestic market. The key determinants of the degree of exchange rate pass through highlighted in the literature are: the imported input share in their production, the market structure, and real and nominal rigidities. A precise understanding of the channels in which exchange rate fluctuations may translate into cost shocks to firms and rigidities that may amplify or diminish firms' responses is critical in promoting price stability.

The other important reason is the liability dollarization, prevalent in emerging markets. A large fraction of their private and public debt is denominated in foreign

[1] With Annie Lee

currency; therefore, the exchange rate fluctuations directly affect the level of indebtedness of emerging economies. More so, upon a large devaluation/depreciation of the domestic currency, emerging economies may face difficulty in servicing their debt, which can consequently bring about private and sovereign defaults. Many of the past studies, empirically and theoretically, have uncovered the contractionary effect of libability dollarization when the domestic currency crashes – Krugman (1999), Céspedes et al. (2004) and Kim et al. (2015).

While the literature has examined those two sets of phenomena extensively, it overlooked how one may affect the other. Specifically, it seldom delves into how liability dollarization may lead to firms' balance sheet deterioration and thereby affect firms' pricing decisions when there is a large depreciation of domestic currency. Such balance sheet deterioration would lead to a sizeable increase in firms' financing costs, an overlooked channel in which exchange rate fluctuations can work as a source of cost shocks. Understanding the role of exchange rate shock as a "cost shock" via not only firms' imported inputs but also through their balance sheets is critical to fully grasp how the exchange rate passes through to domestic prices – the ultimate concern to many central banks in emerging economies.

To have a complete picture of how exchange rate passes through to domestic prices in emerging economies, we analyze both empirically and theoretically the interplay between the exchange rates, the balance sheets of private sectors and their pricing decisions. We highlight how unexpected depreciation of the domestic currency deteriorates firms' balance sheets when they borrow in foreign currency from frictional financial markets, and upon this cost shock we study its implication on their pricing decisions. Our study also complements the recent work on the consequence of financial shocks for domestic prices after the Great Recession in 2007 – Gilchrist et al. (2017), Christiano et al. (2015) and Del Negro et al. (2015). We similarly highlight the role of firms' financial conditions in their pricing decisions, but identifying the very effect by exploiting a large exchange rate devaluation period and varying degrees of foreign currency debt exposure.

In this paper, we first empirically explore the interaction between the balance sheet deterioration and the price dynamics during crisis in emerging economies.

To identify the very effect, we exploit a large devaluation episode in Korea during the Asian Financial Crisis in 1997-98; the price of a dollar in won increased from around 800 won to 1695 won in December 1997 and the average PPI has increased by more than 1.2 folds, as depicted in Figure 2.1. During the policy reforms prior to the crisis on the deregulation of the financial sector and the opening of the capital accounts have fuelled a rapid rise in the total external borrowings from abroad as seen in Figure 2.2.[2] In particular, these reforms eased the regulations on foreign currency borrowings for the short-term securities, increasing the dollar share of business loans from 13% in 1992 to 18% in 1996. When including the offshore loans, loans to Korean firms denominated in foreign currency increased from 20% in 1992 to 28% in 1996 (Cho et al. (2003)).

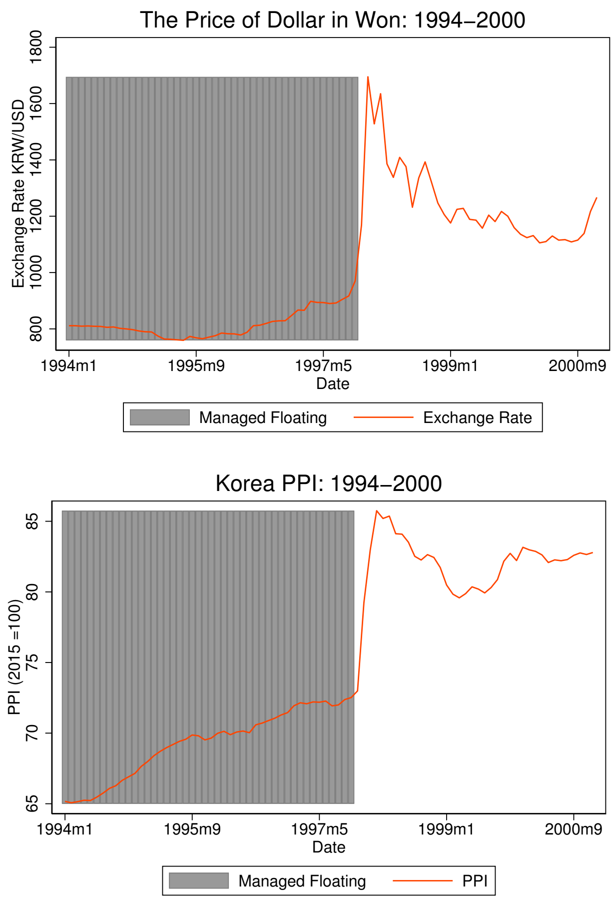
Since firms' expectations on the possibility of floating Korean won were very low and trading financial instruments to hedge against foreign exchange risk was not well established before the crisis, most of these loans were made without an adequate foreign exchange hedging.[3] Hence, firms' accumulation of un-hedged short-term foreign currency liabilities together with unexpected large depreciation gives us a good quasi-natural experiment environment to identify the negative balance sheet effect on domestic prices.

For the analysis, we build a novel dataset that merges the Korean firm-level balance sheet data with industry producer price indices. Most importantly, we construct the industry-level foreign currency debt exposure across manufacturing industries from firm-level balance sheet data. The Korean firm-level data are well-suited to our analysis in that (1) the dataset contains information about their foreign currency liabilities, (2) it not only contains information about large public firms but also small and medium-size firms so it would not under-report the foreign currency exposure of industries populated by smaller firms, and (3) it contains other sets of firm-level variables which allow us to control for potential endogeneity bias.

[2]The deregulation of financial sector has lowered the entry barriers to the financial sector, increasing the number of merchant banks from six to thirty from 1993 to 1996. These merchant banks borrowed in dollar to finance a longer term dollar credit to domestic firms.

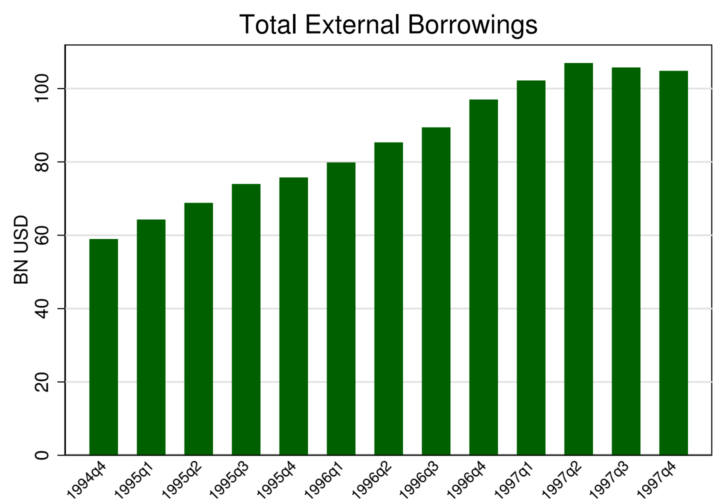
[3]The exchange to trade financial derivatives to hedge foreign exchange risk was first established in 1999 in Korea after the Asian Financial Crisis.

Figure 2.1: Korean won against dollar and PPI: 1994–2000



In our main industry-level empirical analysis, we construct an industy-level foreign currency debt exposure as the weighted average of each firm's short-term foreign currency debt to total debt ratio with their sales share in their industry as weights. In our baseline analysis, we demonstrate that an industry with higher foreign currency short-term debt exposure increased their prices from 1996 to 1998 more than those with lower ratios. Specifically, 1 percentage point increase in industry-level foreign debt exposure leads to 0.48 percentage points larger price change. These results are robust even after controlling for other channels of the pass-through, such as the degree of product differentiation, imported input share

Figure 2.2: Pre-crisis total external borrowings



and price stickiness and other weighted average of firm-level variables such as size, leverage, domestic currency debt ratio and exports to sales ratio.

With rich information on other firm-level variables of our novel dataset, we first investigate whether and to what extent firms with higher foreign currency debt exposure indeed have experienced the deterioration of their balance sheets. Our empirical results corroborate the negative balance sheet effect, documented in the existing literature; firms with higher foreign currency debt experienced lower growth of their sales and net worth. Then, we examine how their estimated price-cost markups have changed during the crisis, which helps us to understand the underlying factors of price dynamics during the crisis. We find that firms with higher foreign currency short-term debt ratio faced lower markup growth. This result is consistent with Christiano et al. (2015) and Del Negro et al. (2015), who argue that financial disruption has increased the cost of production.

Based on the empirical findings, we build a heterogeneous firm model to study an industry equilibrium, analyzing the qualitative and quantitative role of balance sheet channel in shaping the price dynamics across industries. Based on Kohn et al. (2018), we build a model where heterogeneous firms, owned by entrepreneurs, produce differentiated goods by hiring labor and using capital accumulated in previous period. Firms borrow in domestic and foreign final goods but the currency choice is exogenous given by a parameter λ, a share of the foreign debt. The only variation that we look at across industries is the cross-sectional distribution of λ across firms in each industry. Each firm faces a financial constraint on how much one can issue debt, where the maximum amount that they can borrow is less than a fraction of the value of physical capital. In addition, each firm faces a working capital constraint on the amount of wage bill. In our model, a currency depreciation inflates the domestic value of foreign-denominated debt, increasing their debt burden. As a consequence, firms face tighter working capital constraint, which induces higher effective marginal costs. Furthermore, firms reduce their investment, which lowers their labor productivity, leading to higher cost of production. These effects are more pronounced when the financial constraints are binding. Focusing on the effect of the balance sheet channel, we abstract away from the trade channel, which may also affect to the degree of pass-through.

We find that the balance sheet channel is playing a substantial role in explaining the sectoral price dynamics during the crisis. Calibrating the model to match some key moments of Korean manufacturing firm-level data in 1996, we confirm that the model generates the non-targeted moments from the empirical analysis reasonably well. Specifically, we find that around 50% of the observed marginal effect of the foreign currency debt share on the sectoral price change can be explained. This simple model only with the financial friction channel also can explain around 17% of the variation of price changes across industries. The model can generate similar results as in the firm-level empirical analysis.

Lastly, we perform counterfactual exercises (i) by varying cross-sectional distribution of foreign currency debt ratio λ across firms within an industry, while keeping the industry average constant, and (ii) by assuming different preference structure. The experiments reveal an important insight about the role of heterogeneity and strategic complementarity in firms' price settings. Our finding suggests that even though we focus on industry-level price dynamics, if we ignore micro-level heterogeneity such as firm-level distribution of foreign debt holdings or individual firm's markup adjustment, we might underestimate the negative balance sheet effect.

The rest of the paper is organized as follows. The next section describes the related literature and how our work complements previous research. Section 3 outlines our data and shows some summary statistics of firm-level and aggregate industry-level data that we employ. This section also presents the results of our empirical analyses studying the sectoral price dynamics and firm-level performance during the crisis depending on their exposure to the foreign currency debt. Section 4 presents our heterogeneous firm-model. Section 5 calibrates our simple model to study the qualitative and quantitative role of balance sheet channel in shaping the price dynamics across industries and Section 6 studies the model mechanism using individual firm's policy function. Section 7 compares the patterns of the model simulated data with the empirical counterparts and Section 8 performs counterfactual exercises. Then, concluding remarks follow.

2.2 Literature review

This paper is related to a strand of literature studying the interaction of financial frictions and firm's pricing behavior. The absence of the pronounced deflationary pressures during the Great Recession has led to a vigorous research effort focusing on understanding the interaction between firm's price setting behavior and financial frictions. Christiano et al. (2015) and Del Negro et al. (2015) argue that a jump in the credit spread during the Great Recession induces a sharp rise in the cost of working capital, which increases firms' marginal costs – the "cost channel" documented by Barth and Ramey (2001). On the other hand, Gilchrist et al. (2017) focus on alternative markup channel through which the financial constraint affects the pricing decisions of firms. They argue that liquidity constrained firms have increased their markups during the recent financial crisis to make up their liquidity shortage. Using a foreign currency debt exposure prior to the crisis as a proxy for the size of financial shocks during the Asian financial crisis, this paper would provide additional implications on the role of the financial frictions in shaping the price dynamics.

This paper also complements the literature on firms' foreign currency borrowing in emerging markets. Kim et al. (2015) show that Korean firms holding higher foreign currency debt have suffered more during the Asian Financial Crisis: a period of large unexpected currency depreciation among East and Southeast Asian countries. Kohn et al. (2018) study the role of firms' foreign currency debt holding in explaining the dynamics of aggregate exports, output and investment in a large devaluation episode. They argue the foreign currency debt exposure interacting with the financial frictions can explain only a small fraction of the dynamics of exports. Investigating the interaction between foreign currency debt exposure and the price dynamics, this paper provides another important aggregate implication – industry-level price dynamics during a large devaluation episode.

There are several papers investigating endogenous currency debt composition. Salomao and Varela (2018) study the role of firms' foreign currency borrowing on economic growth with endogenous currency debt compositions. They find that firms with high marginal product of capital borrow more in foreign currnecy. Using the Peruvian data, Gutierrez et al. (2020) find that corporates in emerging economies are willing to borrow dollar denominated loans because it is cheaper even after controlling expectations of exchange rate movement. By using Korean firm-level data, Yang et al. (2021) argues that firms with higher export shares tend to borrow in foreign currency more. We take the distribution of foreign currency debt holdings prior to the crisis as exogenous in our model, but we address the potential endogenous bias by controlling various firm-level characteristics in our regressions.

Imported input is one of the most important channels through which the exchange rate fluctuations have an impact on the domestic price dynamics. If a firm uses imported input in its production, currency depreciation is associated with increase in the marginal costs and leads to higher domestic prices. Based on the aggregate industry-level data, Goldberg and Campa (2010) show the domestic CPI sensitivity to exchange rate fluctuations largely depends on the degree of imported input usages. Using a micro-level dataset for the Belgian manufacturing sector, Amiti et al. (2018) emphasize the role of imported inputs and strategic complementarity in shaping the degree of exchange rate pass-through across different industries. Investigating the balance sheet channel through which exchange rate fluctuations would affect to firms' marginal cost, this paper complements the literature on the exchange rate pass-through into domestic prices.

This paper is not the first one to explore the effect of financial frictions on the exchange rate pass-through. With a German firm-level survey dataset, Strasser (2013) empirically shows that financially constrained firms pass through exchange rate changes to domestic prices at almost twice the rate of unconstrained firms. Strasser (2013) focuses on the role of financial frictions on dampening firms' pricing to market behaviour, leading to a higher exchange rate pass-through. In this paper, the level of firms' financial constraints is measured based on their self-assessment of the difficulty of getting credit from banks, different from our analysis focusing on the balance sheet structure. Uncovering the interactions between the foreign-currency debt exposure and the pricing decisions, we study the role of financial frictions as a separate channel, not just dampening or magnifying other channels that the literature focused on when studying the exchange rate pass through on domestic prices.

2.3 Empirical analysis

With the Korean firm-level data, we study the role of the balance sheet channel in shaping the sectoral price changes after the Asian Financial Crisis. Exploiting a large depreciation episode during the Asian Financial Crisis, we first empirically investigate how an industry with higher short-term foreign currency debt exposure changes its price compared to other industries. Then, we turn to our firm-level data of other variables – sales, net-worth, and estimated markup – to investigate potential underlying mechanisms for our sectoral empirical findings.

Our firm-level dataset contains around 3,000 manufacturing firms as of 1996. Considering that the number of publicly listed (all sectors) firms was 760 in 1996, our dataset covers not only large publicly listed firms but also many small and medium-sized firms. Therefore, this dataset is well-suited to measure the sectoral foreign currency exposure because it would not under-report the foreign currency exposure of industries populated by smaller firms. Furthermore, the dataset contains firm-level foreign currency and domestic currency liabilities and their maturity structure, which enable us to build a precise measure of foreign currency debt exposure for each sector and also for each firm, before the crisis unfolds. Lastly, rich firm-level balance sheet information allows us to control for potential endogeneity issues and investigate potential channels of our sectoral level empirical findings.

Data and summary statistics

Our analysis employs a Korean firm-level data from the NICE (formerly the Korea Information Service Inc., KIS). Our dataset includes firms with assets over 7 billion won (around 5.8 million dollar at the current exchange rate) as they need to report their balance sheet information to the Financial Supervisory Commission.[4] The data then are compiled by the KIS.[5] As aforementioned, the KISVALUE dataset has a number of advantages over other datasets: first, it covers a large number of not only large but also small and medium-sized firms, in total around 3,000 manufacturing firms (v.s. 760 publicly listed firms); secondly, it contains the foreign currency split for the short-term and long-term debt.[6] We employ the short-term foreign currency exposure – the ratio of the short-term foreign currency debt to total debt – prior to a large depreciation to measure the level of the financial shock to the firm's balance sheet.

In our KISVALUE dataset, each firm's industry is identified with a five-digit KSIC code (Korea Standard Industrial Classification). Since our main variable of interest is the producer price index (PPI) at the sector-level – four-digit industry code that the Bank of Korea classifies each sector – we first map each KSIC code

[4]Some firms voluntarily report their balance sheet information even when the assets are less than 7 billion won as of 1996. Now, the threshold has gone up to 10 billion won.

[5]All the balance sheet information after 2000 can be found at http://dart.fss.or.kr/.

[6]Bonds are not included in the data.

to the closest PPI industry classification.[7] Then, we aggregate all the firm-level variables at the sector-level, where each sector is an industry defined by the Bank of Korea for its PPI classification. Hence, a *sector* in all our empirical analyses corresponds to an industry defined by the Bank of Korea for PPI. We measure a sector's short-term foreign currency debt exposure as the weighted mean of each firm's short-term foreign currency debt ratio with their sales share in the sector as weights. Hence, a sector with higher foreign currency exposure refers to a sector consisting of more firms with higher short-term foreign currency debt ratio. Other industry-level variables that are aggregated from the firm-level data are defined similarly.

Table 2.1 presents the summary statistics of the firm-level variables that we employ in the analysis. It is noticeable that a 43% of firms hold foreign currency debt and 34.9% of firms hold short-term foreign currency debt in 1996, i.e. it is not just few number of firms holding foreign currency debt. Short-term debt is the amount of debt due within twelve months. Moreover, conditional on holding a positive amount of foreign currency debt, the mean of the foreign currency short-term debt as a ratio of the total debt is 10% in 1996. In 1996, looking at both extensive and intensive margin of the foreign currency debt issuance, a large fraction of firms do borrow in foreign currency, and a substantial fraction of the total debt is denominated in foreign currency given that a firm issues its foreign currency debt.

Before empirically investigating the effect of the balance sheet deterioration on sectoral price changes during the crisis, we first look at how some of the sectoral-level characteristics are correlated with our pre-crisis measure of foreign currency exposure. We consider a number of industry-specific characteristics documented in the literature that may affect the level of exchange rate pass-through into the industrial-level prices. We first consider sector-level degree of product differentiation because sectors producing more differentiated goods tend to show lower

[7] There is no matching code between KSIC codes and PPI industry classification; so, we manually map these two datasets. We map each KSIC code to one PPI industry classification, i.e. one PPI industry classification is mapped to one or a few KSIC codes. The details can be found in the Appendix

Table 2.1: Firm-level summary statistics

	1993	1994	1995	1996	1997	1998
Number of firms	1392	1631	2174	2792	2959	3446
Fraction of firms with FC debt (%)	56.3	53.3	45.7	43.0	40.8	34.5
Fraction of firms with FC short-term debt (%)	49.3	44.7	37.1	34.9	32.0	28.0
Mean FC short-term debt ratio (%)	4.6	3.8	3.5	3.5	3.6	3.2
Mean FC short-term debt ratio given positive holding (%)	9.4	8.6	9.3	10.0	11.0	11.4
Mean log real assets	24.38	24.25	23.9	23.7	23.6	23.3
Mean log real sales	22.9	24.3	24.0	23.9	23.7	23.4
Mean leverage ratio (%)	33.4	33.3	33.9	34.5	36.2	35.8
Mean short-term debt ratio (%)	57.7	57.9	55.2	53.9	51.8	50.2

exchange rate pass-through as noted by Gopinath and Itskhoki (2010). We also consider the imported input share for each sector because a sector with a larger imported input share would face higher costs upon depreciation, which will affect their pricing decisions. We look at whether there is a systemic difference in the foreign currency exposure of the two groups of industries with: (1) high vs. low level of product differentiation and (2) low vs. high share of imported inputs. We use the Rauch classification (Rauch (1999)) to define each industry selling differentiated products or non-differentiated products. Each sector is mapped to multiple Rauch commodities where, for each commodity, a dummy variable has a value of 1 if it is a differentiated product and 0 otherwise.[8] For each sector, we take the weighted average of those dummy variables for commodities mapped to a sector, and the weight is the share of each commodity's trade (both exports and imports) in the total trade volume of all commodities matched to a sector as of 1996.[9] If the weighted average is larger than 0.5, we characterize this industry as

[8]Rauch's classification is at the 4-digit SITC Rev.2 levels. We map SITC code to ISIC Rev.3, following Affendy, Affendy et al. (2010). ISIC Rev.3 is then mapped to ISIC Rev. 4 using the United Nations conversion code. Then, ISIC Rev.4 is mapped to KSIC Rev.10, based on Kim (2008). Since we have mapped each KSIC code to a PPI industry classification, we then have one PPI code mapped to one or multiple SITC 4-digit codes. For more details, please refer to the Appendix

[9]This is following Rauch's method: we implicitly assume that each commodity's importance in the industry is proportional to the trading volume.

differentiated and otherwise *homogeneous*. To compute imported input share for each sector, we use the Input-Output table in 1995 to compute each sector's imported input share.[10]

Table 2.2 and Table 2.3 then summarize the sector-level summary statistics, conditional on the level of product differentiation and the share of imported intermediate inputs. We observe that industries selling homogeneous products and those with high imported input shares have a higher fraction of firms issuing foreign currency short-term debt and higher mean value of foreign currency short-term debt ratio. Given these summary statistics, one might worry that the effect of the foreign currency debt exposure on sectoral price dynamics is a mere consequence of having a higher imported input share and selling a homogeneous product. Thus, to identify the negative balance sheet effect of holding short-term foreign currency debt during a large depreciation episode, we control for the level of product differentiation and imported input share when estimating the marginal effect of the short-term foreign currency debt exposure.[11]

Table 2.2: Level of product differentiation and FC debt exposure

	All	Differentiated	Non-Differentiated
Mean FC short-term debt ratio (%)	3.8	3.0	6.5
Fraction of firms with FC short-term debt (%)	34.9	33.4	45.0

Note: "Differentiated" column refers to the group of differentiated goods sectors as defined by the Rauch classification. "Non-Differentiated" is all other sectors. Mean FC short-term debt ratio and Fraction of firms with FC short-term debt are values as of 1996.

[10] There is no 1996 input-output table at the narrowly defined industry level; so, we used 1995 instead. We manually map one PPI industry classification to one or a few items in the Input-Ouput table. When there are more than one items in the IO table mapped to one sector (one PPI industry classification), we take the average of those imported input shares of items matched, weighted by the total inputs used in each item's production. For more details, please refer to the Appendix

[11] We also control for the price stickiness but the effect is found to be very small.

Table 2.3: Level of imported input share and FC debt exposure

	All	Low-import share	High-import share
Mean FC short-term debt ratio (%)	3.8	2.5	4.6
Fraction of firms with FC short-term debt (%)	34.9	32.5	37.7

Note: "Low-import share" column refers to the group of sectors with imported input share less than 0.5. "High-import share" is all other sectors. Mean FC short-term debt ratio and Fraction of firms with FC short-term debt are values as of 1996. Imported input share is computed using the Input-Output table of 1995 due to data limitation.

FC debt exposure and price dynamics: industry-level regression

The equation (2.1) describes the regression framework of our key empirical finding:

$$\Delta p_i = \beta_0 + \beta_1 \text{ST FC}_{i,1996} + \beta_2 \text{LT FC}_{i,1996} + \beta_3 \text{CHAR}_{i,1996} + \epsilon_i \tag{2.1}$$

The dependent variable is the change in the log of the sector i's price from 1996 to 1998. The main regressors are sector-level short-term foreign currency debt exposure (ST FC) and long-term foreign currency debt exposure (LT FC) in 1996. ST FC and LT FC represent the ratio of short-term foreign currency debt to total debt and the ratio of long-term foreign currency debt to total debt, respectively. To alleviate potential endogeneity concerns, we use the pre-crisis (1996) value of regressors. On the other hand, there might be some concerns about omitted-variables, which may affect both foreign currency debt ratio and the industry-level price change. We deal with this issue in two ways.

First, as aforementioned, we control for other industry-level characteristics, such as the level of the product differentiation, the imported intermediate input share and price stickiness prior to the devaluation episode. Explained in the previous section, we classify each industry selling homogeneous or differentiated goods, based on the method of Rauch (1999). For each commodity, Rauch dummy is equal to 1 when it is a differentiated product and 0 otherwise. Each sector is mapped to multiple Rauch commodities. For each sector, we take the weighted average of those Rauch dummy variables for the commodities matched to a sector, where the weight is the ratio of each commodity's trade (both exports and imports) to total traded volumes of all the commodities matched to a sector in 1996. If the weighted average is larger than 0.5, we characterize this sector as *differentiated* and otherwise *homogeneous*. Imported input share for each sector is computed from the Intput-Output table of 1995. The degree of price stickiness for each industry is measured as the median frequency of price change documented by Nakamura and Steinsson (2008).[12] Other weighted average values of firm-level characteristics are included as well – size, export to sales ratio, domestic currency short-term debt ratio and leverage ratio. We use each firm's sales share in a sector as a weight when computing the weighted averages.

Second, to address the issue of unobserved industry-level characteristics which are not captured by the above variables, we compare the results in the pre-crisis period with those in the crisis period. If the results were driven by the unobserved industry-level characteristics, the relationship between the foreign currency debt holdings and price changes would hold in both pre-crisis and crisis period. Specifically, we run the following regression (2.2) and compare the results with the main regression (2.1):

$$\Delta p_i = \beta_0 + \beta_1 \text{ST FC}_{i,1993} + \beta_2 \text{LT FC}_{i,1993} + \beta_3 \text{CHAR}_{i,1993} + \epsilon_i \tag{2.2}$$

The dependent variable is the change in the log of the sector i's price from 1993 to 95 and the regressors are of 1993 values. We also control for industry-level characteristics as in regression (2.1).

Table 2.4 summarises the regression estimates of the crisis period. Column 1 is without controlling any of the industry characteristics: when an industry shows higher short-term foreign currency debt exposure, its price goes up by more upon a large devaluation. Specifically, when the short-term foreign currency debt exposure goes up by 1 percentage point, the changes in price is 0.48 percentage points higher. As we control other industry-level characteristics, the number goes down to 0.38; however, it still has a significant impact on price changes even after controlling

[12] For more details on mapping and calculations, please refer to the Appendix

Table 2.4: Industry price dynamics and short-term FC debt ratio (crisis period)

	(1)	(2)	(3)	(4)	(5)
ST FC	0.481***	0.437**	0.365**	0.478***	0.377**
	(0.176)	(0.191)	(0.164)	(0.178)	(0.183)
LT FC	0.061	0.121	0.107	0.075	0.133
	(0.185)	(0.180)	(0.175)	(0.185)	(0.176)
Rauch dummy		-0.068**			-0.046*
		(0.026)			(0.027)
Imported input share			0.195***		0.137*
			(0.066)		(0.074)
Degree of price stickiness				0.001	-0.000
				(0.002)	(0.002)
R^2	0.190	0.237	0.238	0.192	0.256
N	157	149	157	157	149

Note: This table shows the results from regression (2.1) with different set of regressors. The dependent variable is the change in the log of the sectoral price from 1996 to 1998. The main regressors are sector-level short-term foreign currency debt exposure (ST FC) and long-term foreign currency debt exposure (LT FC) in 1996. To alleviate potential endogeneity issue, we use the pre-crisis (1996) value of regressors. For the imported input share, we use 1995 value due to data availability. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient estimate is significantly different from zero at 10%, 5% and 1% level, respectively.

other factors documented in the literature. The signs of the control variables are as expected: as an industry's product is more homogeneous and having a higher input share, the change in prices is higher. The price stickiness does not seem to have a significant impact, but this might partially come from the broad classification that the degree of price stickiness is defined over, in contrast to our industry classification, which is more narrowly defined (four-digit).[13]

Table 2.5 shows the results in the pre-crisis period. In contrast to the estimates in Table 2.4, there is no evidence of negative balance sheet effect on sectoral price changes. The size of coefficient estimates on short-term foreign currency debt ratio

[13] We also have controlled for the changes in the number of firms in each industry, which may have some implications on the industrial price dynamics during the crisis. The results are shown in Table 13 in the Appendix. The main results are robust to controlling for changes in the level of competition which may occur when firms exit during the crisis.

Table 2.5: Industry price dynamics and short-term FC debt ratio (pre-crisis period)

	(1)	(2)	(3)	(4)	(5)
ST FC	0.147	0.115	0.098	0.157	0.121
	(0.144)	(0.132)	(0.145)	(0.135)	(0.134)
LT FC	0.151	0.191	0.154	0.136	0.158
	(0.215)	(0.205)	(0.210)	(0.202)	(0.192)
Rauch dummy		-0.073*			-0.069*
		(0.038)			(0.041)
Imported input share			0.129*		0.050
			(0.075)		(0.082)
Degree of price stickiness				-0.001	-0.002
				(0.001)	(0.001)
R^2	0.056	0.097	0.078	0.057	0.106
N	151	144	151	151	144

Note: This table shows the results from regression (2.2) with different set of regressors. The dependent variable is the change in the log of the sectoral price from 1993 to 1995. The main regressors are sector-level short-term foreign currency debt exposure (ST FC) and long-term foreign currency debt exposure (LT FC) in 1993. To alleviate potential endogeneity issue, we use the 1993 value of regressors. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient estimate is significantly different from zero at 10%, 5% and 1% level, respectively.

fall by more than half and the estimates are not statistically different from zero. Furthermore, the regression based on the pre-crisis period in Table 2.5 shows much smaller R^2 compared to the baseline regression in Table 2.4, which implies the explanatory power of pre-crisis industry-level characteristics including foreign currency debt exposure is not as significant as that of large devaluation episodes. From these empirical findings, we can ascertain that the effect of the short-term foreign currency debt exposure is not a consequence of some spurious relationship but comes from the negative balance sheet effect upon the exchange rate depreciation shock.

Since the literature on the exchange rate pass-through into domestic prices focuses largely on the import channel, as a robustness check, we additionally control for changes in imported input prices in 1996-98. We use the import price indices and the input-output table of 1995 from the Bank of Korea. For an industry, we use

Table 2.6: Balance sheet channel independent of imported input channel

	(1)	(2)	(3)
ST FC	0.437**	0.377**	0.389**
	(0.191)	(0.183)	(0.185)
LT FC	0.122	0.133	0.125
	(0.181)	(0.176)	(0.175)
Imported input share		0.137*	
		(0.074)	
Imported input price change			0.372**
			(0.180)
R^2	0.237	0.256	0.259
N	149	149	149

Note: This table shows the results from regression (2.1) with different set of regressors. The dependent variable is the change in the log of the sectoral price from 1996 to 1998. The main regressors are sector-level short-term foreign currency debt exposure (ST FC) and long-term foreign currency debt exposure (LT FC) in 1996. To alleviate potential endogeneity issue, we use the pre-crisis (1996) value of regressors. For the imported input share, we use 1995 value due to data availability. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient estimate is significantly different from zero at 10%, 5% and 1% level, respectively.

the input-output table to compute each input's share in the total imported inputs. Then, using these shares as weights, we compute the weighted average of imported input price changes in 1996-98. It measures each industry's imported input price changes during the crisis. Prices of some inputs might have increased more than other inputs, which will increase the imported input costs disproportionately across industries. Table 2.6 summarizes the results. Column 1 reports the baseline results without variables that capture the imported input channels but controlling for other industry-level characteristics, Rauch dummy and price stickiness and also weighted average of firm-level variables– size, export to sales ratio, domestic currency short-term debt ratio and leverage ratio. In Column 2, we include the imported input share, computed from the input-output table of 1995 – which is identical to that in Column 5 of Table 2.4. The estimated coefficient of foreign currency debt exposure falls but not to a large extent. Moreover, Column 3 shows that even when controlling for increase in input price changes in 1996-98, the estimated coefficient doesn't fall, and the estimate is still significant at 5% level. From the regression analyses, we show that the balance sheet channel works as an independent channel through which an industry experiences higher pass-through into their domestic prices.

Inspecting mechanism: firm-level regression

With a richer information on other firm-level variables of our novel dataset, we further investigate whether and to what extent firms with higher foreign currency debt exposure indeed have experienced the deterioration of their balance sheet during the crisis. We use log change of sales and net worth to quantify the degree of balance sheet deterioration during the crisis period as in Kim et al. (2015). In addition, we provide empirical evidence on a mechanism through which negative balance sheet effect is transmitted into firm-level pricing behavior. To be specific, we explore whether the firm-level changes of price-cost markup are related with firm-level foreign currency exposure during large devaluation episode. In the literature, there are two competing channels through which financial disruption can induce price increase. First, Christiano et al. (2015) and Del Negro et al. (2015) argue that a spike in the credit spread during the Great Recession induced a sharp rise in firms' marginal costs. Financial shocks increase marginal costs and hence deteriorates the competitiveness of individual firms, lowering their price-cost markup. On the other hand, Gilchrist et al. (2017) focuses on alternative markup adjustment channel through which the financial friction affects the pricing decision. In their model, liquidity constrained firms increase their markups to make up their liquidity shortage. Explicitly investigating the price-cost markup behavior of individual firms with high foreign currency exposure, we evaluate the price adjustment mechanism.

The below is the firm-level empirical specification that we adopt for the rest of the exercise.

$$\begin{aligned}\Delta y_{j,96-98} = {} & \beta_0 + \beta_1 \text{ST FC}_{j,1996} + \beta_2 \text{LT FC}_{j,1996} + \beta_3 \text{Size}_{j,1996} \\ & + \beta_4 \text{ST FC}_{j,1996} \cdot \text{Size}_{j,1996} + \beta_5 \text{LT FC}_{j,1996} \cdot \text{Size}_{j,1996} + \beta_6 \text{CHAR}_{j,1996} + \epsilon_j\end{aligned}$$

as explained above, y_j variables that we examine are: firm-level log real sales, log net-worth, and log markup.[14] The dependent variable is a change in y_j from 1996 to 1998. ST FC and LT FC are firm-level short-term and long-term foreign currency debt to total debt ratio, respectively. We control for the firm-level characteristics such as size (measured by log of total assets), export to sales ratio, domestic currency short-term debt ratio and leverage ratio to deal with a potential endogeneity issue. Price-cost markups are computed following De Loecker and Warzynski (2012). We also interact with the firm size to see if the balance sheet effect would be smaller for large firms who are less financially constrained compared to small ones, following Kim et al. (2015). Our main coefficients of interest are β_1 and β_4 in each regression.

Table 2.7: Firm's performance during the crisis

Δy_{96-98}	(1) Sales growth	(2) Net worth growth	(3) Markup growth
ST FC	-7.749***	-5.679**	-0.914***
	(1.547)	(2.333)	(0.302)
LT FC	-1.777	-2.010	0.497
	(1.911)	(1.858)	(0.396)
Size	-0.153***	-0.046	0.000
	(0.031)	(0.037)	(0.008)
Size * ST FC	0.321***	0.205**	0.034***
	(0.061)	(0.090)	(0.012)
Size * LT FC	0.094	0.085	-0.020
	(0.076)	(0.076)	(0.016)
R^2	0.212	0.086	0.069
N	2237	2237	2237

Note: This table shows the results from firm-level regressions. The dependent variables are the change of (1) log real sales, (2) log net-worth, and (3) log markup from 1996 to 1998. The main regressors are firm-level short-term foreign currency debt ratio (ST FC) and cross product between size and ST FC in 1996. The size is measured as the log of real assets. To alleviate potential endogeneity issue, we use the pre-crisis (1996) value of regressors. Robust standard errors are calculated in paranthesis. *, **, and *** indicate that the coefficient estimate is significantly different from zero at 10%, 5% and 1% level, respectively.

Table 2.7 summarizes the firm-level regression results. As we can see in Columns

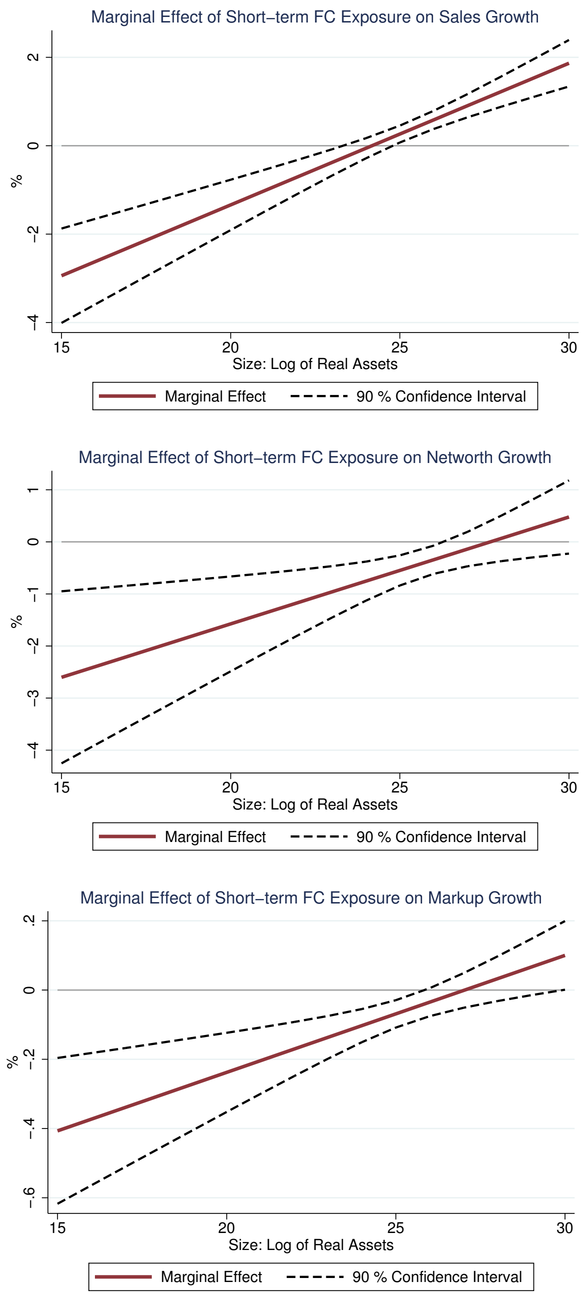
[14]Nominal series are deflated with CPI to compute real series.

(1) and (2), firms with higher short-term foreign currency debt suffers a larger decline in sales and net-worth, which shows the deterioration of their balance sheets during the crisis. The negative effect is mitigated as firm size is larger since firms are less financially constrained. To be specific, one percentage point increase in short-term foreign currency ratio is associated with 0.165 percent decrease in sales of an average-sized firm. When firm size becomes smaller by one standard deviation, the effect is amplified by 0.46 percentage points. For the net-worth, one percentage point increase in short-term foreign currency ratio is associated with 0.96 percent decrease in net worth of an average sized firm. When firm size becomes smaller by one standard deviation, the effect is amplified by 0.3 percentage points.[15] This finding is consistent with the result of Kim et al. (2015). Column (3) shows how each firm's markup growth has changed to see if a larger increase in the sectoral level price changes with higher foreign currency exposure is a consequence of (a) an increase in markup or (b) a rise in marginal cost. The regression result supports the latter: a price rise upon a deterioration of the balance sheet is more associated with a rise in marginal costs rather than a markup increase. Specifically, one percentage point increase in short-term foreign currency debt exposure is associated with 0.1082 percent decrease in price-cost markup of average size firms. When firm size becomes smaller by one standard deviation, the effect is amplified by 0.05 percentage points. Figure 2.3 shows a complete picture of how the marginal effects of short-term FC exposure on the growth of the firm-level variables vary across firm sizes.

Lastly, in Figure 2.3, we observe that the negative effect of short-term foreign currency exposure on the net-worth changes lingers even for large firms, while the marginal effects on the growth of sales and price-cost markup flip to positive when the firm size is two standard deviations above the mean. Within an industry, even when a firm experiences a fall in its networth – deterioration of its balance sheet, relatively less worse-off firms performed well during the crisis. This empirical pattern reveals how firms strategically interact within a sector and how a larger firm size may cushion the effect of higher debt burden when holding foreign currency

[15] The average and the standard deviation of firm sizes are 23.7 and 1.45, respectively.

Figure 2.3: Marginal effect of short-term FC exposure on firm-level variables



debt, and this strategic interaction within a sector leads to a positive growth in sales, and markups despite its fall in networth. Hence, we believe that it is important to have strategic interactions between firms and explore their effects on the aggregate price dynamics in our structural model.

In sum, we find that during the large devaluation episode, firms with higher foreign currency debt exposure have experienced larger balance sheet deterioration, and larger drop of price-cost markup.[16] Based on these results, we build up a structural model where a large foreign currency debt exposure together with a large depreciation leads to an increase in firms' marginal costs. More details are described in the next section.

2.4 Model

In this section, we build a heterogeneous firm model to interpret the empirical findings and quantify the balance sheet effect on industry price dynamics during the crisis. Even though our industry- and firm-level empirical analysis provide a clear evidence on the negative balance sheet effect, it mainly relies on the cross-sectional variation in the data and focuses on the relative changes across industries and firms. Hence, the model provides a clear understanding of the underlying channel based on the empirical analysis and helps us to quantify the importance of balance sheet deterioration in explaining the aggregate industry-level price dynamics upon a large devaluation. Specifically, we would like to qualitatively and quantitatively study to what extent the observed disparity in foreign currency exposure across industries explains the average of and the dispersion in the industry-level price changes upon a large depreciation during the Asian Financial Crisis.

Our model is based on Kohn et al. (2018). We consider an industry equilibrium model where heterogeneous firms, owned by entrepreneurs, produce differentiated goods and issue one-period non-defaultable debt, of which a fraction (firm-specific) is denominated in foreign final goods. Each firm has a different level of foreign

[16] In the appendix, we confirm the result is similar for other firm-level variables: investment, labor-productivity, employment.

currency debt ratio, exogenously given in our model. The only variation across industries in our model is the *industry-specific* firm-level distribution of foreign currency debt ratios which is disciplined by the empirical counterpart. Each firm faces two types of financial frictions. First, firms face financial constraint on how much one can issue debt, determined by a fraction of capital. Second, when firms produce output, they face working capital constraint that requires non-interest-bearing assets for the wage bill payment as in Uribe and Yue (2006). We will assume that the economy is in the stationary equilibrium before an unexpected real exchange rate depreciation. Our focus is on the transition dynamics of the price changes.

Market Structure

We assume that each industry I faces an exogenous CES demand, where the demand for industry I's composite goods is given by:[17]

$$Y_I = P_I^{-\nu}\bar{Y}$$

Each industry is populated by a continuum of entrepreneurs indexed by j with a measure of 1. The technology of transforming intermediate goods into industry I's composite goods is characterized by the Kimball (1995) aggregator:

$$\int \Upsilon\left(\frac{y_j}{Y_I}\right) dj = 1$$

The Kimball demand structure gives the demand for an intermediate good produced by an entrepreneur j:

$$y_j = \psi\left(D_I \frac{p_j}{P_I}\right) Y_I \quad \text{where} \quad \psi(.) = \Upsilon'^{-1}(.),\ D_I \equiv \int \Upsilon'\left(\frac{y_j}{Y_I}\right)\frac{y_j}{Y_I} dj$$

[17] We assume that $\bar{Y} = 1$ without loss of generality.

Following Gopinath and Itskhoki (2010), we assume the following functional forms:

$$\psi(x_j) = \left(1 - \epsilon \ln(\frac{\sigma x_j}{\sigma - 1})\right)^{\sigma/\epsilon}, \text{where } x_j = D_I \frac{p_j}{P_I}$$

Then, the demand for an intermediate good produced by an entrepreneur j:

$$y_j = \left(1 - \epsilon \ln(\frac{\sigma x_j}{\sigma - 1})\right)^{\sigma/\epsilon} Y_I \text{ where } x_j = D_I \frac{p_j}{P_I}$$

$$p_j = \frac{\sigma - 1}{\sigma} \exp\left(\frac{1}{\epsilon}\left(1 - (\frac{y_j}{Y_I})^{\epsilon/\sigma}\right)\right) \frac{P_I}{D_I}$$

$$P_I = \int p_j \left(1 - \epsilon \ln(\frac{\sigma x_j}{\sigma - 1})\right)^{\sigma/\epsilon} dj$$

Using the Kimball aggregator, we would like to capture the strategic complementarity between firms in their pricing decisions, and see how the model predictions are aligned with what we have seen from the data. Moreover, we can talk about variable markups with the Kimball aggregator, which would not be possible with the nested CES demand structure. Gopinath and Itskhoki (2010) show that the first order deviation from D_I from its steady state value $\bar{D} = \frac{\sigma-1}{\sigma}$ is zero. Following Gopinath and Itskhoki (2010), we use the first-order approximation to the industry price level:

$$\ln P_I = \int \ln p_j \, dj$$

Firm's technology

Each firm j in industry I produces a differentiated intermediate good, $y_{j,I}$ and sells at price $p_{j,I}$ in a monopolistically competitive market.[18] We assume each firm faces an Kimball demand structure, characterized by two parameters σ and ϵ as we describe in the previous subsection.[19] Firms produce differentiated goods with the

[18] From here on, we will simplify the notation by dropping industry and firm indices I and j, and we will use them only when needed for clarification.

[19] We normalize the aggregate price, aggregate output and aggregate wage to one.

production technology $y_t = z_t k_t^{\alpha} n_t^{1-\alpha}$, hiring labor n_t and physical capital k_t. z_t is an idiosyncratic productivity that follows AR(1) process, $\ln(z_t) = (1-\rho_z)\mu_z + \rho_z \ln(z_{t-1}) + \epsilon_t$, where ϵ_t is normally distributed with zero mean and standard deviation σ_ϵ. We discretize the idiosyncratic shock process following Tauchen (1986). In our model, we assume that firms are neither exporting nor importing to shut down the trade channel and focus on the effect of the financial channel.

Each entrepreneur owns a firm and maximizes the expected sum of discounted utility from final goods consumption with relative risk aversion, γ:

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma}$$

An entrepreneur is endowed with a unit of labor and supplies one's labor inelastically at a competitive wage. Each entrepreneurs accumulate physical capital which is subject to convex adjustment cost $\Phi(k_t, k_{t+1})$ by investing x_t amount of final goods capital. Physical capital in this model has two modes: production and collateral.

In the beginning of the period, entrepreneurs learn this period's productivity z_t and the exchange rate ξ_t. Then, they hire labor n_t, produce and sell differentiated goods y_t at price p_t, pay back the old debt and issue new debt d_{t+1}, and choose next period's level of capital k_{t+1} and working capital a_{t+1}.

Entrepreneurs can borrow by issuing two types of one-period debt, one denominated in domestic final goods and other in foreign final goods. Since both are non-defaultable, they are sold at the same risk-free price $\frac{1}{1+r}$. The model is abstract away from the portfolio choices and the share of foreign debt is exogenous and pre-determined at the **firm-level**. Since the agents in the economy expect that the exchange rate will be constant before and after the one-time unexpected exchange rate shock hits, there is no UIP deviation. Hence, including portfolio choice in the model will not determine the share of foreign currency debt, justifying our assumption on the exogeneity of the foreign currency debt share.

Each industry has a different distribution of foreign currency debt exposure λ

and this is the *only* variation across industries in our model. The average foreign currency debt ratio for industry I is determined by the distribution of λ_j across firms in industry I. We approximate the distribution by assuming a finite number of values that λ can take, $\{\lambda_m : m = 1, 2, \ldots, n\}$, with the industry-specific probability mass function of $\{\pi_m^I : m = 1, 2, \ldots, n\}$. We calibrate λ_m and π_m^I to match the data counterparts, which will be explained in more details in the calibration section. In the model, the average foreign currency debt ratio of an industry I will be defined as: $\bar{\lambda}_I = \sum_m \lambda_m \pi_m^I$.

We analyze how much a variation in $\bar{\lambda}_I$ that we observe from the data can explain the dispersion in the price changes across sectors upon a large unexpected depreciation as in the data. The real exchange rate ξ_t is exogenous and defined as the price of foreign final goods in units of domestic final goods. A firm chooses to borrow d_{t+1} (in units of domestic final goods) at the price $\frac{1}{1+r}$ where $(1-\lambda)\frac{d_{t+1}}{1+r}$ is denominated in domestic final goods. Then, each entrepreneur holds $\lambda\frac{d_{t+1}}{1+r}\frac{1}{\xi_t}$ amount of the foreign debt in units of foreign final goods in period t. In the beginning of the following period, each entrepreneur pays back $(1-\lambda)d_{t+1}$ for domestic debt and $\lambda d_{t+1}\frac{\xi_{t+1}}{\xi_t}$ for foreign debt in units of domestic final goods.

Entrepreneurs face a borrowing constraint where they can only borrow upto a fraction θ of the capital. Thus, the amount that each entrepreneur can borrow hence is as follows:

$$\frac{d_{t+1}}{1+r} \leqslant \theta k_{t+1}.$$

In addition, each entrepreneur faces working capital constraint. Specifically, in order to finance their wage bill payment $w_t n_t$, firms need to hold non-interest-bearing asset a_t that is chosen from the previous period. Hence, the amount of wage bill each entrepreneur can pay is limited as:

$$w_t n_t \leqslant a_t.$$

Recursive formulation and equilibrium

An entrepreneur's problem is then summarized as follows:

$$v(k,d,a,z,\lambda) = \max_{c\geqslant 0,d',k',a',n,p} \frac{c^{1-\gamma}}{1-\gamma} + \beta E_{z'}[v(k',d',a',z',\lambda)]$$

$$\text{s.t.} \quad (a)\ c + k' + \Phi(k,k') + a' + d\big((1-\lambda) + \lambda\frac{\xi}{\xi_{-1}}\big) = py - wn + (1-\delta)k + \frac{d'}{1+r} + a$$

$$(b)\ \frac{1}{1+r}d' \leqslant \theta k', \quad (c)\ wn \leqslant a$$

where

$$(i)\ y = \left(1 - \epsilon \ln(\frac{p}{P_I})\right)^{\sigma/\epsilon} P_I^{-\nu}, \quad (ii)\ y = zk^{\alpha}n^{1-\alpha}$$

$$(iii)\ \Phi(k,k') = \frac{\phi}{2}(\frac{k' - (1-\delta)k}{k})^2 k$$

We define a recursive stationary industry equilibrium as (i) industry I's price P_I and output Y_I, (ii) a set of policy functions $\{d', k', a', c, n, y, p\}$, value function $v(k,d,a,z,\lambda)$, and (iii) a measure ψ_I on (k,d,a,z,λ) satisfying:

1. Policy and value functions solve the firm's problem.

2. Industry output market clears.

$$\ln P_I = \int \ln(p(k,d,a,z,\lambda))d\psi_I(k,d,a,z,\lambda)$$

$$Y_I = \Big(\int y(k,d,a,z,\lambda)^{\sigma/\epsilon} d\psi_I(k,d,a,z,\lambda)\Big)^{\sigma/\epsilon}$$

3. A measure ψ_I is consistent and stationary.

We assume that the economy is in a stationary industry equilibrium prior to the unexpected depreciation of the real exchange rate. We study the transition dynamics of different industries upon the unexpected depreciation of the real exchange rate, where industries are characterized by different foreign debt exposure. Note that without aggregate shocks (when $\frac{\xi}{\xi_{-1}} = 1$) in the stationary equilibrium, the recursive problem does not depend on the value of λ; hence, each industry has the same stationary equilibrium but different transition dynamics upon unexpected depreciation of the real exchange rate.

2.5 Calibration

Table 2.8 summarizes the parameter values that we use for the quantitative exercise. The first half of the parameters are either from the literature or directly computed from the data we have. Most importantly, we set λ_m and π^I_m to match the cross-sectional distribution of foreign currency debt ratio across firms for each industry.

We first set $\{\lambda_m : m = 1, 2, \ldots, 21\} = \{0\%, 2.5\%, 7.5\%, 12.5\%, ...97.5\%\}$, which are the median values of 21 bins: $\{\lambda = 0, 0 < \lambda \leqslant 5, 5 < \lambda \leqslant 10, \ldots, 95 < \lambda \leqslant 100.\}$ Then, for each industry, we calibrate the $\{\pi^I_m : m = 1, 2, \ldots, 21\}$ to approximate the distribution. We use the sales weighted probability mass function when calibrating π^I_m. $\bar{\lambda}_I = \sum_m \lambda_m \pi^I_m$ represents the average industry-level foreign currency debt exposure. This way it is consistent with the way that we have computed the average foreign currency debt ratio for each industry in the industry-level empirical analysis. To see if there is any substantial round-up error, we compare $\bar{\lambda}_I$ and the data counterpart – the actual weighted mean of each firm's ratio of short-term foreign currency debt to total debt with the weight as one's sales revenue. We find that their correlation is close to one.

Following Ackerberg et al. (2006), we estimate the firm-level productivity process using our data outside the model. ρ_z and σ_z that we have estimated are 0.9 and 0.07 respectively. We discretize the process following Tauchen (1986). Due to limited data availability, with the monthly observations of three-year government bond yields and the realized inflation rates in 1996, we compute the real rate by taking the mean of three-year government bond yields and subtracting the mean of the realized inflation rates. We set the value of capital adjustment cost ϕ as 0.9569 following Gilchrist and Sim (2007) who use the same Korean firm-level data (KIS) as we used.

For the calibrated parameters, i.e. the discount factor β and the fraction of capital used as collateral θ, we find the parameters that minimize the distance between the model and data moments. The model moments are computed in the stationary industry equilibrium, where there is no exchange rate shock and thus, the value of λ does not play a role in computing the stationary equilibrium. The targeted moments are the cross-sectional mean and standard deviation of leverage ratios across firms in 1996, 0.595 and 0.21 respectively in the data.

Table 2.8: List of parameter values

Predetermined			
Parameter	**Value**	**Description**	**Data Source**
γ	2.0	Relative risk aversion	Standard
ν	2.0	Elasticity of substitution across sectors	Standard
δ	0.1	Depreciation rate of physical capital	Standard
ϕ	0.9569	Physical capital adjustment cost	Gilchrist and Sim (2007)
σ	5.0	Elasticity of substitution within a sector	Gopinath and Itskhoki (2010)
ϵ	4.0	Super elasticity of demand	Gopinath and Itskhoki (2010)
r	0.08	Interest rate	Bank of Korea
ρ_z	0.9	AR coefficient of z	Estimated
σ_z	0.07	STD of z	Estimated
λ_m	0 – 0.975	Distribution of FC debt share	Estimated from KIS data
π^I_m		Distribution of FC debt share	Estimated from KIS data

Calibrated			
Parameter	**Value**	**Description**	**Targeted Moments**
β	0.92	Time discount factor	Mean of Leverage Ratio = 0.595
θ	0.727	Fraction of capital as a collateral	Std of Leverage Ratio = 0.21

For the real exchange rate, we compute the changes from 1996 to 1998. Following the actual dynamics of the real exchange rate after the Asian Financial Crisis, we simulate the economy upon the unexpected shock where ξ increases from 1 to 2.1 in the first period and stays there afterwards. We effectively assume one-time unexpected negative shock to the real exchange rate *returns* but assume zero expected returns afterwards.[20] Hence, there will be no deviation from the UIP

[20]The depreciation in the first period is unexpected but they know that in the future $\xi/\xi_{-1} = 1$.

condition. Upon this so-called MIT shock, we compute the transition dynamics, focusing on the industry-level prices.

2.6 Inspecting mechanism: policy function analysis

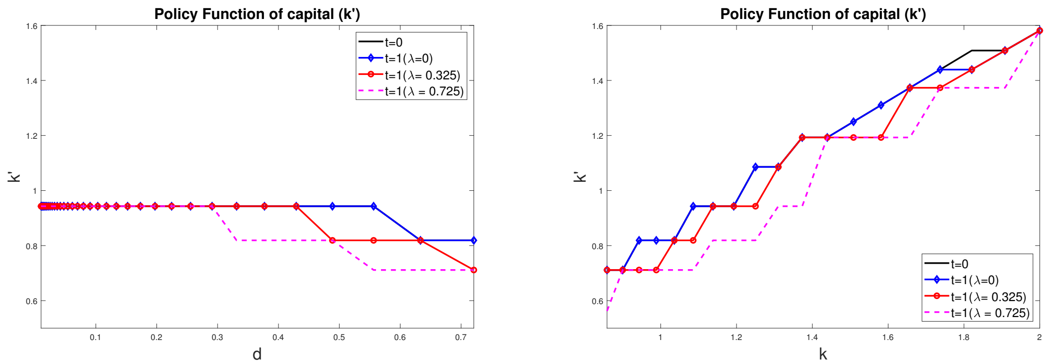
We first examine firm-level policy functions to explore the underlying mechanism of pricing decision. All parameters are set to our calibrated values summarized in Table 2.8. In the model, balance sheet deterioration has an effect on firm's pricing decision through (i) investment adjustment and (ii) working capital constraint. When firms invest less, they become less productive in the next period, increasing their marginal cost of production. Furthermore, tighter working capital constraint implies higher effective marginal cost of production, leading to higher prices. Therefore, we begin by investigating the investment decisions and working capital constraints under the steady state and on the transition path upon a large devaluation. In this analysis, we look at an industry I with the cross-sectional distribution of foreign currency debt ratio across firms $\{\pi_m^I : m = 1, 2, \ldots, 21\}$, which we get from the data counterpart as aforementioned in Section 5. We fix idiosyncratic productivity z at the median level. In addition, when we plot policy functions against initial debt level d, we fix the level of k and a at $k = k_{mod}$ and $a = a_{mod}$. Likewise, when we plot policy functions against initial capital stock k, we fix the level of d and a at $d = d_{mod}$ and $a = a_{mod}$. [21]

Figure 2.4 shows the policy functions of k'.[22] In the left panel, we find that when firm's debt burden is too high, the borrowing constraint starts binding, which lowers next period capital stock. Hence, higher debt burden is associated with lower investment. The right panel shows that next period's capital stock becomes larger when a firm holds more initial capital stock. This result illustrates that borrowing constraint is less binding for larger firms, and hence they do not reduce their investment as much as they would if their initial capital stock was low. Furthermore,

[21] We try different distribution of foreign currency debt holdings $\{\pi_m^I : m = 1, 2, \ldots, 21\}$ and different values of z, k, and d, but the results are qualitatively the same.

[22] Note that the policy function is the same for all λ in the stationary equilibrium.

Figure 2.4: k' against (i) d (Left) and (ii) k (Right).



Note: The black solid lines are the policy functions in the stationary equilibrium. Blue-diamond lines, red circle lines and magenta dashed lines are policy functions for firms with 0, 0.325 and 0.725 of foreign currency debt ratio respectively.

Figure 2.4 shows the effect of a large depreciation on firm-level capital stock. For any given amount of foreign currency debt, firms need to pay more in units of domestic goods due to a large depreciation. This higher debt burden lowers firm's investment. When a firm's reliance on foreign currency debt was large prior to the crisis, increase in debt burden will be more pronounced, lowering its investment more.[23]

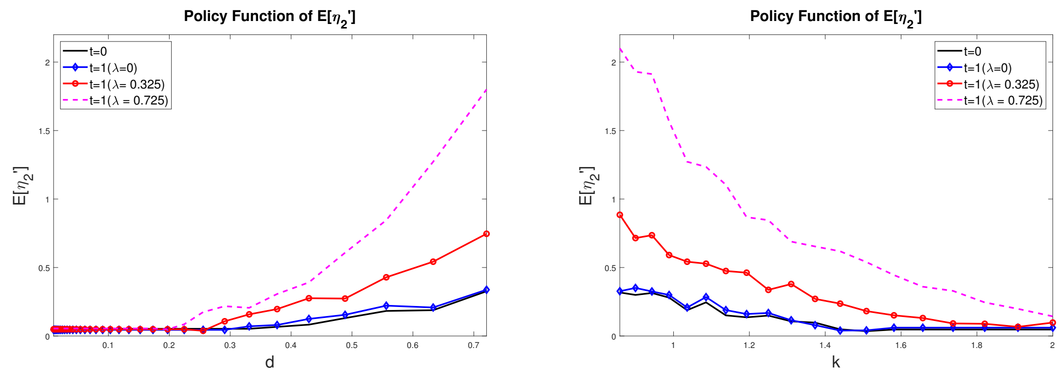
In order to understand working capital channel, we begin the analysis by relating the firm's Euler equations regarding debt choice d' and working capital a' as follows

$$\beta E_{z'}[(c')^{-\gamma}(1+r)\big((1-\lambda)+\lambda\frac{\xi'}{\xi}\big)]+\eta_1=\beta E_{z'}[(c')^{-\gamma}+\eta_2'] \tag{2.3}$$

where η_1 and η_2 are Lagrange multiplier on collateral constraint: $\frac{1}{1+r}d' \leqslant \theta k'$, and working capital constraint: $wn \leqslant a$, respectively. Equation (2.3) shows that even for the non-binding collateral constraint case $\eta_1 = 0$, any positive value of net interest rate, i.e., $(1+r)E_{z'}[\big((1-\lambda)+\lambda\frac{\xi'}{\xi}\big)]-1>0$, implies that the working-capital constraint always binds, i.e., $E_{z'}[\eta_2'] > 0$. More importantly, when the collateral constraint becomes tighter, i.e., $\eta_1 > 0$ increases, it has direct effect on the

[23]In both panel, the policy functions of firms with zero FC holdings under steady state and transition path coincide each other.

Figure 2.5: $E_{z'}[\eta_2']$ against (i) d (Left) and (ii) k (Right).



Note: The black solid lines are the policy functions in the stationary equilibrium. Blue-diamond lines, red circle lines and magenta dashed lines are policy functions for firms with 0, 0.325 and 0.725 of foreign currency debt ratio respectively.

Lagrangian multiplier $E_{z'}[\eta_2']$ on working capital constraint. Because firm's optimal labor decision is determined by

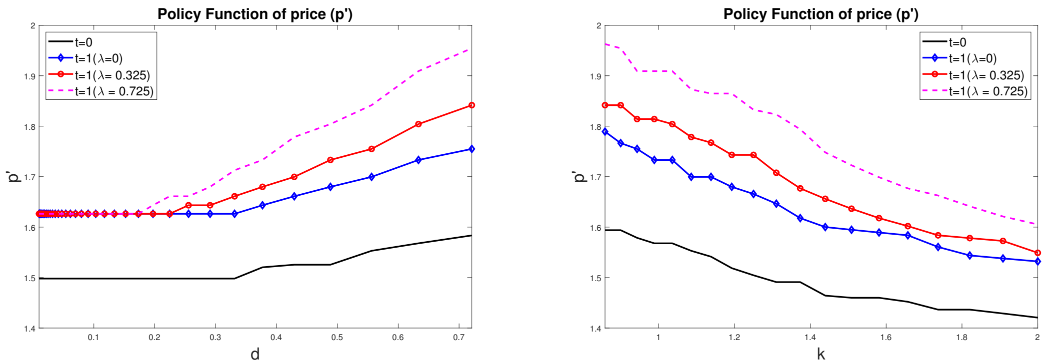
$$\big(p'(y)y + p(y)\big)(1-\alpha)k^{\alpha}n^{-\alpha} = w + \eta_2,$$

today's tighter collateral constraint (higher η_1) implies higher next-period effective wage costs (higher $w' + E_z'[\eta_2']$), leading to higher next-period prices.

Figure 2.5 plots the Lagrangian multiplier $E_{z'}[\eta_2']$ in order to analyze the negative balance sheet effect on working capital constraint. In the left panel, we find that firm's working capital constraint becomes tighter when its debt burden is higher. Furthermore, when a firm's reliance on foreign currency debt was large prior to the crisis, the working capital constraint becomes tighter, which leads higher effective cost of labor. Similar to the investment decision, the right panel shows that the balance sheet effect is weaker for the firms with larger size.

Figure 2.6 illustrates how firms change their prices upon a large devaluation. Left panel shows the pricing decision as a function of initial debt level. In all cases, when debt burden becomes larger, firms tend to charge higher prices. Furthermore, firms who have higher foreign currency debt holding increase their price more

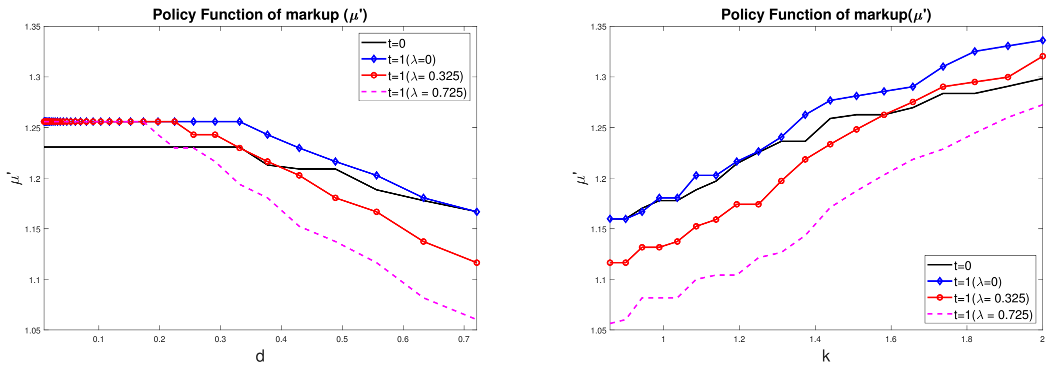
Figure 2.6: p' against (i) d (Left) and (ii) k (Right).



Note: The black solid lines are the price policy functions in the stationary equilibrium. Blue-diamond lines, red circle lines and magenta dashed lines are policy functions for firms with 0, 0.325 and 0.725 of foreign currency debt ratio respectively.

when the domestic currency becomes cheaper. This result echoes the findings in Figure 2.4 and Figure 2.5 that higher debt burden translates into lower level of capital stock and tighter working capital constraint. If a firm invests less in this period, they become less productive in the next period in terms of its labor productivity, which increases its cost of production. Hence, they will charge higher prices. Furthermore, tighter working capital constraint implies higher effective marginal cost of production, amplifying the price increase. The right panel in Figure 2.6 shows the pricing decision as a function of initial capital stock. Consistent with the findings in Figure 2.4 and Figure 2.5, when firms hold more initial capital stock, they increase price less and when firms hold more foreign currency debt, they increase their price more upon large depreciation. In addition to the negative balance sheet effect, we find that strategic complementarity plays an important role in determining firm-level pricing decisions in both panels. Even if firms are not directly affected by the devaluation when holding zero foreign currency debt, they will set the price higher than what they have chosen at the steady state. This result arises from strategic complementarity due to the Kimball preference, which makes firms raise their next-period price because they expect their competing firms will increase prices. Therefore, in our model, firms increase their prices not only because of the direct effect from their balance sheet deterioration, but also due to the strategic complementarity to their competitors' charging higher prices.

Figure 2.7: μ' against (i) d (Left) and (ii) k (Right).



Note: The black solid lines in both graphs show the markup policy functions under steady state. Blue-diamond lines, red circle lines and magenta dashed lines are policy functions for firms with 0, 0.325 and 0.725 of foreign currency debt ratio respectively.

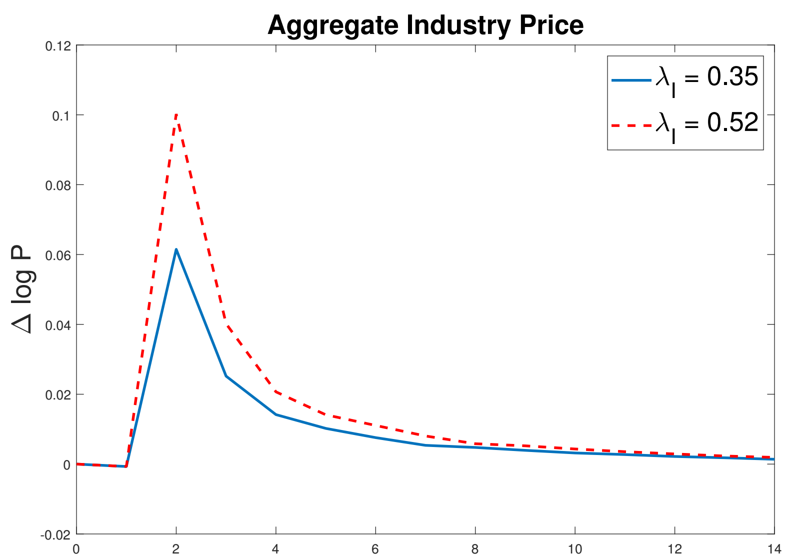
Lastly, we investigate how firm-level markup changes upon a large depreciation. In both panels in Figure 2.7, we find that if a firm holds larger foreign currency debt on its balance sheet, it will charge lower markup when the domestic currency becomes cheaper. This result is consistent with the findings in Figure 2.4 and Figure 2.5 that increase in debt burden leads to a lower level of capital stock and tighter working capital constraint. If a firm invests less this period, they become less productive in the next period in terms of labor productivity, increasing the costs of production. Hence, they become less competitive and so charge smaller markup. At the same time, tighter working capital constraint leads to higher effective marginal cost of production, making firms less competitive. We also find that some firms indeed increase their markup upon large devaluations compared to the level of markup at the steady state. The negative balance sheet effect is not strong enough to those firms because their initial level of debt was small enough or their initial level of capital stock was large enough. Hence, they become more competitive just because they are not affected by the large depreciation as much as their competitors have.

2.7 Sectoral price dynamics in the model and the data

Industry-level analysis

This section summarizes the results from the model simulations of 149 industries with the parameter values calibrated. We first investigate the transition path of each industry price upon a large unexpected depreciation in period 1. Figure 2.8 depicts the transition path of the industry prices for two sectors with different average share of the foreign currency debt to total debt, $\bar{\lambda}_I$: 0.52 and 0.35. After a large depreciation of the domestic currency, those industries experienced price increase by around 10% and 6 %. Given that those industries have actually experienced 55% and 49% of price increase during the crisis period, respectively, our quantitative model is able to explain a significant share of price responses only through the balance sheet channel. As an industry has a higher exposure to foreign currency debt, it increases its price more after the real exchange rate depreciates unexpectedly.

Figure 2.8: Impulse response functions of industry prices



Industry-level transition paths are the consequence of the negative balance sheet effects and the strategic complementarity between firms in the same industry as seen from the policy functions in the previous section. Firms with a high-level of foreign currency exposure face larger debt burden upon a large unexpected depreciation; hence, it reduces investment more and faces tighter working capital constraint, which leads to a more pronounced price increase. The very effect is stronger when firms are more financially constrained due to lower initial capital or higher initial debt before the crisis. On top of that, the Kimball demand structure allows firms strategically interact each other, which amplifies the price responses of firms to the balance sheet deterioration. In our model, smaller firms with lower capital k experience a larger increase in marginal costs due to the financial constraints. With this negative correlation of firm size and an increase in marginal costs, the with-in industry strategic complementarity in pricing leads to a higher increase in the industry price Amiti et al. (2018). The role of strategic complementarity in amplifying the price responses is well illustrated in the next section.

Table 2.9: Marginal effect of FC short-term debt ratio on price changes in crisis

	Data	Model
ST FC	0.377^{**}	0.1862^{***}
	(0.175)	
R^2	0.1895	0.9930
N	149	149

To compare the model results with the data patterns, we first run the same regression that we run for the empirical section. We first compute the price changes (log difference) from period 0 to period 2 for each industry, and regress it to $\bar{\lambda}_I$. As can be seen in Table 2.9, the coefficient estimate is 0.1862, where the data counterpart is 0.377. The model explains around 50% of the mean effect of the short-term foreign currency debt on the price changes across industries. We also compute the standard deviation of the log price changes from 1996 to 1998 across industries and its model counterpart and find 0.1188 and 0.02 respectively. Our simple model - with an only variation across industry in their foreign currency exposure - can explain around 17% of the variation in price changes during the Asian Financial Crisis. We would like to emphasize that all these numbers were not targeted in our calibration, and hence its quantitative size shows how well the model captures the sectoral price dynamics during the crisis and also the cross-sectional variation in price changes across industries who had varying degrees of exposure to the foreign currency debt.

Firm-level analysis

Using our structural model, we simulate firm-level data for 149 industries (14,900,000 firms), pool all the simulated data, and run the regression to qualitatively compare with the data patterns. With simulated data, we further investigate the role of financial constraints in shaping the price dynamics upon the shock. We run the below regression specifications:

$$(3): \Delta y_j = \beta_0 + \beta_1 ST\ FC_j + \beta_2 1_{\text{Constrained},j} + \beta_3 ST\ FC_j \times 1_{\text{Constrained},j} + \epsilon_j$$
$$(4): \Delta y_j = \beta_0 + \beta_1 ST\ FC_j + \beta_2 \log(k_j) + \beta_3 ST\ FC_j \times \log(k_j) + \epsilon_j$$

ST FC is the short-term foreign currency debt ratio of firm j, which is λ in our model. β_1 and β_3 are the main coefficients of interest. In the model, we observe if firms are financially constrained and not. Thus, we first directly use this information to analyse the role of the financial constraint in amplifying the negative effect of high foreign currency debt ratio on their balance sheet upon a large depreciation. We use the indicator function, $1_{\text{Constrained},j}$, to indicate that whether a firm j is financially constrained when making their borrowing decisions after the shock hits. Then, we use the same variable as our reduced-form analysis, log of assets, which in our model correspond to capital holdings when the shock hits.[24] The correlation between two measures is -0.4836, implying larger firms are less financially constrained.

[24]We use the capital stock chosen one period before the shock hits but nothing qualitatively changes when we use the capital stock chosen when the shock hits.

Table 2.10 and Table 2.11 summarize the regression results of specifications (3) and (4). Both results clearly show the amplification effect from the financial constraint on the price changes. Firms that are financially constrained increase their prices when they have the same level of foreign currency exposure on their balance sheets. Moreover, as they increase prices more, due to our Kimball demand structure, their competitiveness in the market goes down, leading to a fall in markups. These findings are qualitatively consistent with what we see from the firm-level regression in Section 3.

Table 2.10: Firm-level regression: role of financial constraint

	Price Changes	Markup Changes
ST FC	-0.003	0.004
$1_{\text{Constrained},j}$ * ST FC	0.098	-0.096

Table 2.11: Firm-level regression: role of firm size

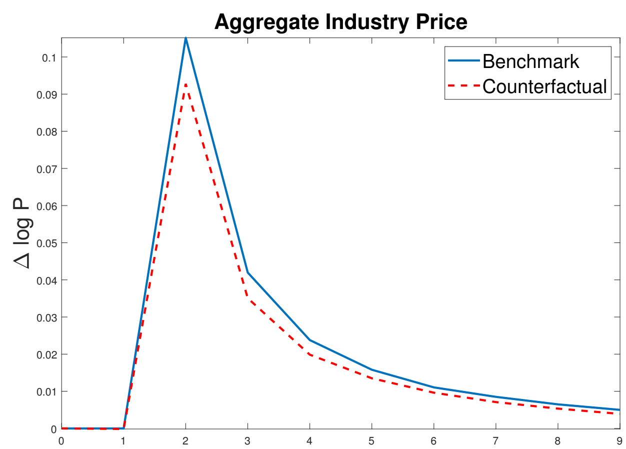
	Price Changes	Markup Changes
ST FC	0.038	-0.036
$\log(k_j)$ * ST FC	-0.090	0.085

In sum, we construct a heterogeneous firm model that links the foreign currency debt exposure and price dynamics upon a large depreciation. The model is able to account for the industry-level empirical patterns – larger price increase when an industry is on average holding higher foreign currency debt ratio. Moreover, from firm-level simulations, we confirm that the model can explain the observed firm-level behavior upon large devaluation well. We have shown that firms increase their prices and reduce their markups as they have higher foreign currency debt exposure especially more so when they are financially constrained.

2.8 Counterfactual analysis

In this section, we perform counterfactual exercises (i) by varying cross-sectional distribution of foreign currency debt ratio λ across firms within an industry and (ii) by assuming different preference structure. The first experiment illustrates the importance of heterogeneity in foreign currency debt ratio λ across firms. From the second experiment, we compare the industry price responses of the baseline economy with the Kimball demand to the one the CES demand structure to highlight the role of strategic complementarity in their pricing decision.

Figure 2.9: Impulse responses of industry prices under Kimball preference

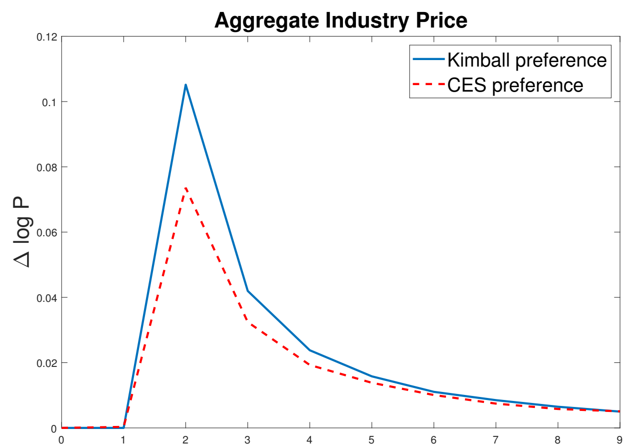


Note: The average value of the foreign currency debt ratio, $\bar{\lambda}_I$, is 0.514.

We start the analysis by comparing the benchmark economy, which has the distribution of λ matched to the data counterpart to a counterfactual economy, which has a counterfactual distribution of λ aross firms. To be specific, we construct the counterfactual distribution as follows. First, we choose a benchmark industry whose empirical distribution of λ shows some dispersion in the foreign currency debt across firms and with a significant average share of foreign currency debt. Then, we calculate the average value $\bar{\lambda}_I$ of that particular industry and assume all firms hold the same level of foreign currency debt share $\lambda = \bar{\lambda}_I$. In the counterfactual economy, we shut down firm-level heterogeneity of foreign currency debt holding within an industry.

Figure 2.9 illustrates the role of firm-level heterogeneity of foreign currency debt holding in amplifying the effect of a large devaluation on the industry price changes. Upon an unexpected large devaluation, the benchmark industry experiences around 10.2 percent increase in price. The counterfactual industry shows large but dampened responses (9.2 percent) compared to the benchmark one. This result suggests that not only the average level of foreign currency debt ratio $\bar{\lambda}_I$, but the heterogeneity in λ within an industry has an effect on the industry-level price dynamics.

Figure 2.10: Impulse responses of industry prices: Kimball vs. CES



Note: The average value of the foreign currency debt ratio, $\bar{\lambda}_I$, is 0.514.

In Figure 2.10, we perform an additional exercise to highlight the role of strategic complementarity in amplifying the sectoral price responses. Specifically, we compare the industry price responses of the baseline economy with the Kimball demand to the one the CES demand structure, which shuts down the strategic interactions between firms. In the CES demand, firms always charge a constant markup and so there is no strategic complementarity in their pricing decisions. As seen in Figure 2.10, once we shut down the strategic complementarity, the price increases only by 7.5 percent, which is much dampened response compared to the price change in the benchmark case under the Kimball preference (10.2 percent).

This result illustrates that the strategic interaction between firms amplifies the negative balance sheet effect on the sectoral price responses. In sum, in this section, we find that even though we focus on industry-level price dynamics, if we ignore detailed micro-level heterogeneity such as firm-level distribution of foreign debt holdings or individual firm's markup adjustment, we might underestimate the negative balance sheet effect.

2.9 Conclusion

With a unique firm-level and aggregated industry-level dataset, our empirical findings suggest that the balance sheet channel – whose role is understudied in the exchange rate pass-through literature – plays an important role in explaining how the exchange rate affects domestic prices, especially for emerging economies with dollarized liabilities. We find that industries with higher foreign currency debt increased their prices more during the crisis. Then, we look at how firm-level variables had changed during the crisis when a firm had high exposure to foreign currency debt. Our firm-level empirical investigation confirms the negative balance sheet effect, where firms faced lower growth in sales and net worth when holding a high level of foreign currency debt before the crisis. Moreover, our firm-level analysis shows that the markups seem to have *declined* more for those with higher foreign currency debt, suggesting that the marginal cost channel is the main driver of the effect of the foreign currency debt exposure on price changes.

Based on these empirical findings, we build a quantitative heterogeneous firm model to study an industry equilibrium model and its transition path when there is an unexpected exchange rate depreciation. We analyze the qualitative and quantitative implications of the financial frictions in explaining the average changes in the sectoral prices and its dispersion. With the industry-specific firm-level distribution of foreign currency debt and the real exchange rate shocks, both of which are matched from the data, the model can explain around 50% of the effect of the foreign currency debt ratio on the price changes and 10% of the variation in price changes across industries. Our model is also able to generate a quantitatively sizable price increase for those with a high level of foreign currency exposure: for an industry with the highest foreign currency exposure, in our model, the price increase during the crisis is around 17%, which is 18 percent of what we see from the data. Moreover, our firm-level regressions with simulated data are able to match the qualitative patterns that we have found with our firm-level data. Lastly, we have investigated the role of strategic complementarity and heterogeneity in the foreign currency debt holdings across firms within an industry. When we compare our benchmark economy with the counterfactual economy, where all the firms hold the same level of foreign currency holdings equal to the average level in that industry, the price increase during the crisis is lower when there is no heterogeneity in firms' foreign currency holdings. We also see how the strategic complementarity plays a role by comparing our baseline economy with Kimball demand structure to the one with CES demand structure. We find a much dampened response with the CES demand, revealing how with-in industry strategic complementarity in pricing leads to a higher increase in the industry prices.

Our empirical analysis and our structural model reveal that it is important, albeit overlooked, to incorporate the balance sheet effect when analyzing how the exchange rate affects domestic prices, especially for emerging economies whose liabilities are dollarized. Our findings have important policy implications for policymakers on shaping the optimal monetary policy and currency choice in external borrowings. We believe that it is an important normative question to ask, but we will leave it for future research.

Appendix A

Appendix: Chapter 1

A.1 Data cleaning

In the main empirical analysis, we merge Compustat Fundamentals Quarterly data with Compustat Segment and CRSP. Sample period is from 1987Q1 to 2017Q4. Data cleaning and construction process closely follow Ottonello and Winberry (2020), Bharath and Shumway (2008) and Decker et al. (2016).

First, we exclude firm observations with following properties.

- Firms are in finance, insurance, and real estate sectors ($sic \in [60, 67]$) and public administration ($sic \in [91, 97]$)
- Firms are not incorporated in the U.S.
- Firms with observation less than 40.

Firm-quarter observations with following properties are also excluded.

- Investment rate belonging the top and bottom 0.5 percent of the distribution.
- Leverage higher than 10.
- Liquidity belonging the top and bottom 0.5 percent of the distribution.
- Current asset to total asset ratio higher than 10 or below -10.
- Quarterly real sales growth rate higher than 1 or below -1.
- Acquisitions larger than 5% of total assets.

- Missing and non-positive value of capital stock (**ppentq**), sales (**salesq**), or total assets (**atq**).
- Missing leverage.

The investment is measured as $\Delta \ln(k_{i,t+1}) = \ln(k_{i,t+1}) - \ln(k_{i,t})$, where $k_{i,t+1}$ is the real book value of capital stock of firm i at the end of period t. To construct the measure of capital stock, the perpetual inventory method is used. Specifically, for each firm, the initial value of capital stock is set by the first reported value of gross plant, property, and equipment (**ppegtq**) of each firm. Then, the series of $k_{i,t+1}$ is computed recursively using the changes of net plant, property, and equipment (**ppentq**):

$$k_{i,t+1} = k_{i,t} + ppentq_t - ppentq_{t-1}$$

Before the process, capital stock is deflated by the non-residential fixed investment good deflator taken from NIPA table. For the missing value of capital stock (**ppenqt**), we impute as follows. If firm's ppentq is missing but the values right before and after the missing value are nonmissing, it is estimated by linear interpolation. If two or more consecutive observation are missing, there is no imputation.

As a proxy of the firm size, the log of sales (**saleq**) or the log of total asset (**atq**) are used. Both are deflated by Implicit Price Deflators for Gross Domestic Product from NIPA table. Another set of variables capturing the firm-level characteristic consists of the leverage, the liquidity, sales growth rate, current asset (**atcq**) to total asset ratio and the number of markets a firm access to. Leverage is the debt to total asset ratio, where the debt is the sum of short-term (**dlcq**) and long-term (**dlttq**) debt. Liquidity is defined as the ratio of cash and short-term investment (**cheq**) to total asset. Sales growth rate is measured as the log-differences in real sales. In order to calculate the number of lines of busienss (the number of different industries firms are operating in), we use Compustat Segment. Since this variable is available in Compustat Segment which only provides an annual frequency data, in a given year, quarterly values are filled-in by using the corresponding yearly value. To construct a distance to default measure, we closely follow Bharath and Shumway (2008). First, we defind the firm-level variable distance to default (dd) as follows

$$dd \equiv \frac{\ln(V/F) + (\mu - \sigma^2/2)}{\sigma}$$

where V is the total value of the firm, μ is the annual expected return on V, σ is the annual volatility of the firm's value, and F is the face value of firm's debt (short-term debt (dlcq) plus one-half of long-term debt (dlttq)). In this procedure, it is crucial to estimate the measure of V and we follow an iterative method by Bharath and Shumway (2008).

Step 1. Set a guess V_j for V. For the initial guess V_0, we use the sum of firm's debt and equity, i.e. $V_0 = E + F$, where E is the firm's stock price times the number of shares (both items are available from CRSP).

Step 2. Estimate the mean μ and variance σ^2 of return of the guessed firm's value $\Delta \ln(V_j)$ over $T = 250$-day moving window.

Step 3. Obtain a new estimate of V_{j+1} from the Black-Scholes-Merton option-pricing framework. Specifically, we find V_{j+1} such that

$$E = V_{j+t1}\Phi(\delta_1) - e^{-rT}F\,\Phi(\delta_2)$$

where $\delta_1 \equiv \dfrac{\ln(V_{j+1}/F) + (\mu - \sigma^2/2)T}{\sigma^2\sqrt{T}}$, $\delta_2 = \delta_1 - \sigma\sqrt{T}$, and r is the daily one-year constant maturity Treasury-yield.

Step 4. Compare V_j and V_{j+1}. If they are close enough, we are done. Otherwise, we repeat the procedure from step 1 with V_{j+1} as a new guess.

Figure A.1: Comparison with VIX index

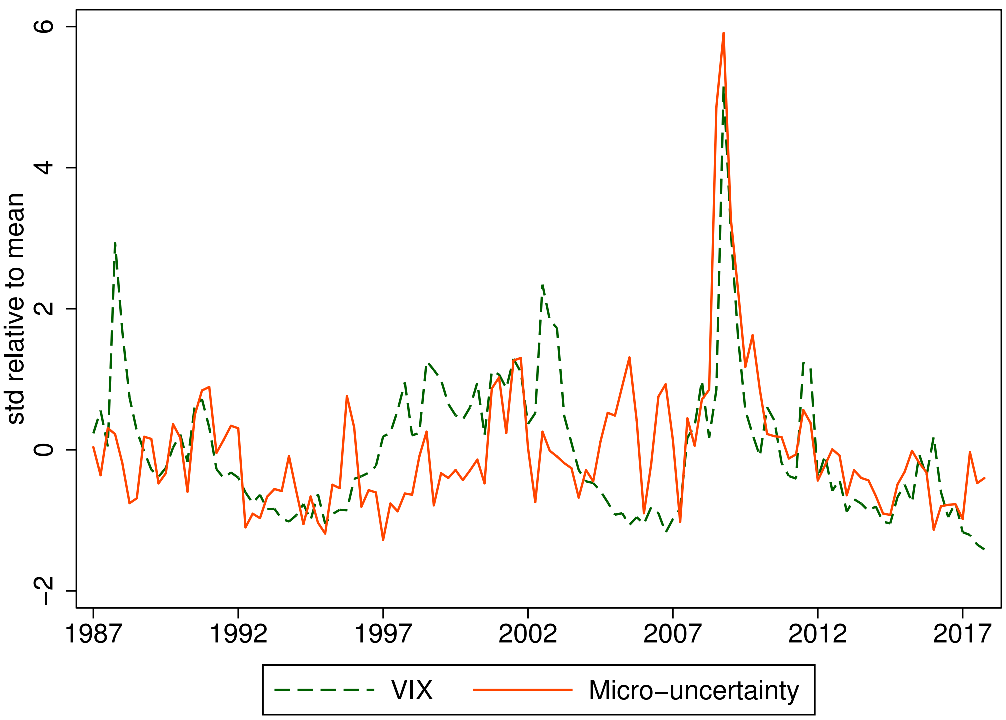


Table A.1: Robustness check

Dependent variable: $\Delta \log k_{j,t+1}$

	(1)	(2)	(3)	(4)	(5)
size × uncertainty	0.209***	0.319**	0.295**	0.296**	0.275**
	(0.052)	(0.157)	(0.131)	(0.144)	(0.125)
size × GDP growth		0.010			
		(0.022)			
size × interest			0.027		
			(0.072)		
size × inflation				0.023	
				(0.107)	
size × unemp					0.024
					(0.035)
Observations	235,695	240,724	240,724	240,724	240,724
R^2	0.314	0.113	0.113	0.113	0.113

Notes: column 1 uses different investment measure $\frac{i_{j,t}}{k_{j,t-1}}$ and column 2 - 5 controls for different cyclicalities. Standard errors in parentheses are two-way clustered by firm and time. We standardize the size measure over the entire sample. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

Table A.2: Uncertainty and the number of lines business

Dependent variable: $\Delta\log(\mathtt{lob}_{j,t+1})$	
uncertainty	**-0.084**
	(0.068)
gdp growth	-0.000
	(0.000)
interest rate	0.226***
	(0.062)
inflation rate	-0.001*
	(0.001)
unemployment rate	0.001***
	(0.000)
Observations	301,460
R^2	0.030

Notes: dependent variable is the log change of the number of lines of business. Each line of business means each industry a firm operates in. Standard errors in parentheses are two-way clustered by firm and time. $*$, $**$, and $***$ indicate that the coefficient estimate is significantly different from zero at 10%, 5%, and 1% significance level, respectively, based on standard normal critical values for the two-sided test. The sample period is from 1987Q1 to 2017Q4, and all firms in Compustat are used for the analysis except those in finance, insurance, real estate and public administration sectors.

A.2 Model computation

In the model section, we solve (i) stationary equilibrium, (ii) impulse responses under partial equilibrium and (iii) impulse responses under general equilibrium. Because we assume representative household's preference as

$$\ln C - \theta N, \quad \theta > 0$$

the wage w is determined by

$$w = \frac{\theta}{U_C} = \theta C.$$

Hence, in order to solve equilibirum, we need to keep track of either U_C or w. We define $p \equiv U_C$ which is the intertemporal price of consumption goods. As in Bloom et al. (2018), this approach enables us to redefine firm's problem in terms of household's marginal utility, which allows us to solve the model relatively simpler. For instance, we transform following incumbent single-unit firm's problem

$$V^S(z,k;\mathbf{S}) = \max_{d,n,k'} \; d - w(\mathbf{S})\psi(d;\mathbf{S}) + E\Big[m(\mathbf{S},\mathbf{S}')V_0^S(z',k';\mathbf{S}') \mid z;\mathbf{S}\Big]$$

into

$$\tilde{V}^S(z,k;\mathbf{S}) = \max_{d,n,k'} \; p(\mathbf{S})(d - w(\mathbf{S})\psi(d;\mathbf{S})) + \beta E\Big[\tilde{V}_0^S(z',k';\mathbf{S}') \mid z;\mathbf{S}\Big].$$

We solve firm's problem by using value function iteration. We set up the grid following $k_i = k_{i-1}/(1-\delta)$ to ensure the depreciated value of k_i to coincide with k_{i-1} and choose the lower and upper bound of grid points of k large enough to prevent firms to choose the boundary points.

Staionary equilibirum economy

Step 1. Guess a general equilibrium price $p = U_c$.

Step 2. Given the guess, solve for incumbent single- and multi- unit firm's and entrant single- and multi- unit firm's problem.

Step 3. Obtain time invariant measure of μ_S and μ_L from (i) incumbent and entrant firms' optimal choices and (ii) distribution of idiosyncratic productivies.

Step 4. Compute aggregate variables based on firm-level optimal choices and time invariant measure of μ_S and μ_L. If the implied aggregate consumption $C = Y - I$ is consistent with the guessed value of $p = U_c$, we are done. Otherwise, we update p based on bi-section method and redo the whole process until it converges.

Impulse response functions under partial equilibrium

We fix the equilibrium price $\bar{p} = \bar{U}_C$ and $\bar{w} = \theta/\bar{p}$ at the steady-state level, which is derived from the previous section. Then, we solve individual firms problem given the prices and exogenous processs of aggregate TFP and uncertainty. For instance, we solve the single-unit firms problem as follows

$$\tilde{V}^S(z, k; A, \sigma) = \max_{d,n,k'} \bar{p}(d - \bar{w}\psi(d; A, \sigma)) + \beta E\left[\tilde{V}_0^S(z', k'; A', \sigma') \mid z; A, \sigma\right].$$

where We solve the incumbent multi-unit firm's problem and entrant single- and multi- unit firm's problems in a similar way. Then, we simulate 2000 independent economies with 100 quarters. For each economy i, starting from the stationary distribution without any aggregate shocks, we switch on all exogeneous shocks to aggregate TFP and uncertainty, allowing them to evolve normally according to the stochastic processes described in the previous sections before period 45. At period 45, we artificially impose a high value of uncertainty (or low TFP). After the shock period, the exogenous processes evolve normally again from period 46. In each period, we repeatedly calculate the cross sectional distribution of single- and multi-unit firms and calculate aggregate variable of interest X_{it}. With simulated series of $\{X_{it}\}$, we define the time t response of X to an exogenous shock as

$$\hat{X}_t = 100 \times \ln\left(\frac{\bar{X}_t}{\bar{X}_{44}}\right),$$

where $\bar{X}_t$ is the level of cross-economy mean: $\frac{1}{2000}\sum_i X_{it}$.

Impulse response functions under general equilibrium

To calculate impulse response functions under general equilbrium, we need to solve the model with exogenous shocks and endogenous prices. In this case, the infinite-dimensional distributions become state variable of individual firms, which is known to be big challenge to solve the model without approximation. Hence, our model solution heavily relies on the numerical method by Krusell and Smith (1998). In this method, we assume that market price p and aggregate capital stock K follow approximate log-linear rules as;

$$\ln(p) = \alpha_p(A, \sigma, \sigma_{-1}) + \beta_p(A, \sigma, \sigma_{-1})\ln(K)$$

$$\ln(K') = \alpha_K(A, \sigma, \sigma_{-1}) + \beta_K(A, \sigma, \sigma_{-1})\ln(K)$$

In order to find the approximate law of motion for price and aggregate capital stock, we solve the model as follows.

Step 1. Guess the approximate law of motions for p and K as

$$\ln(p) = \alpha_p^{(j)}(A, \sigma, \sigma_{-1}) + \beta_p^{(j)}(A, \sigma, \sigma_{-1})\ln(K)$$

$$\ln(K') = \alpha_K^{(j)}(A, \sigma, \sigma_{-1}) + \beta_K^{(j)}(A, \sigma, \sigma_{-1})\ln(K)$$

Step 2. Given the guess, solve for individual firm's problem. For instance, a single-unit firm solves

$$\tilde{V}^S(z, k; A, \sigma, \sigma_{-1}, K) = \max_{d,n,k'} \; p(A, \sigma, \sigma_{-1}, K)(d - w(A, \sigma, \sigma_{-1}, K)\psi(d; A, \sigma, \sigma_{-1}))$$

$$+\beta E\left[\tilde{V}_0^S(z', k', K'; A', \sigma', \sigma) \mid z; A, \sigma, \sigma_{-1}, K\right].$$

Step 3. After solving all firms' problem, simulate the economy by allowing all exogenous shocks to evolve normally.

Step 4. Based on the simulated aggregate data of $\{p_t^{(j)}\}$ and $\{K_t^{(j)}\}$ from step 3, update the log-linear maping to get the new coefficient in the approximate law of motion for p and K:

$$\alpha_p^{(j+1)}(A, \sigma, \sigma_{-1}),\; \beta_p^{(j+1)}(A, \sigma, \sigma_{-1}),\; \alpha_K^{(j+1)}(A, \sigma, \sigma_{-1}),\; \beta_K^{(j+1)}(A, \sigma, \sigma_{-1}).$$

Step 5. If the coefficients are close enough to the guessed values, we are done. Otherwise, we update the guess.

Given the converged approximate law of motion for p and K, and firm's optimal decisions, we calculate the impulse response functions as in previous section.

Appendix B

Appendix: Chapter 2

B.1 Data source

The below table summarizes the data sources of variables that we employ in the empirical section.

Data	Data Source	Note
Firm-level variables	KISVALUE	
Producer Price Index (PPI)	Bank of Korea	Base year of 2015
Rauch Classification	Rauch (1999)	4-digit SITC Rev. 2 commodities
Imported Input Share	Bank of Korea	Input-Output (IO) table of 1995
Price Stickiness	Nakamura and Steinsson (2008)	Median frequency of price change in Table 12
Imported Input Price Changes	Bank of Korea	Import Price Indices and IO Table for Imports of 1995

B.2 Data merging

Our analysis focuses on the manufacturing sector. A *sector* in our empirical analysis corresponds to a most narrowly defined group that the Bank of Korea computes each PPI – which we will from now on call as a PPI industry classification. In other words, *a sector is a PPI industry classification*. All the matching work is to merge data at the PPI industry-level.

Firm-level data matching

In KISVALUE dataset, each firm's industry is identified with a five-digit KSIC (Korea Standard Industrial Classification) code. There is no matching code available between KSIC codes and PPI industries. We manually map those two datasets.

We map each KSIC code to the closest PPI industry classification. As a result, one PPI industry classification is now matched to none, one, or a few KSIC codes. Hence, those firms with different KSIC codes, but mapped to the same PPI industry classification, are now treated as they are in the same sector. For each sector, S, we compute X_S, the weighted average of a firm-level variable of interest, x_i, as:

$$X_S = \sum_{i \in S} x_i \frac{y_i}{Y_S} \text{ and } Y_S = \sum_{i \in S} y_i$$

where S is a sector (PPI industry classification) and y_i is firm i's sale and Y_S is the total sales of firms in sector S.

Rauch classification

For each of commodities at the 4–digit SITC Rev.2 levels, Rauch (1999) defines whether it is a differentiated product or not. Following Affendy, Yee and Satoru (2010), we map each 4–digit SITC code to a ISIC Rev.3 code. It means that one ISIC Rev.3 code is mapped to none, one or a few 4–digit SITC codes. Then, following the United Nation's conversion table, we map each ISIC Rev.3 code to *one or more* ISIC Rev.4 codes. This implies not only that one ISIC Rev.3 code is now mapped to one or a few ISIC Rev.4 codes but also that one ISIC Rev.4 code is now mapped to one or a few ISIC Rev.3 codes.[1] Next, we map each ISIC Rev.4 code to a KSIC Rev.10 code, following Kim (2008). In this mapping, exactly one ISIC Rev.4 code is matched with one KSIC Rev.10 code. From the above section, we describe that one PPI industry classification is mapped with none, one or a number of KSIC Rev.10 codes. Hence, now we have one PPI industry classification is mapped to none or one or a few of 4–digit SITC Rev.2 codes.

For each commodity at the 4–digit SITC code Rev.2 level, we define a dummy variable that it is equal to 1 if it is a differentiated product. Then, for each sector (PPI industry classification), we take the weighted average of those binary num-

[1]This is a N:N matching.

bers, where the weights are the commodities' trade shares in 1996.[2] We define each sector's product as *differentiated* when this weighted average is above 0.5 and *homogeneous* otherwise.

Input-Output table and import price index

We use the Input-Ouput (IO) table in 1995 from the Bank of Korea. We map each PPI industry classification to one or two closest items in the IO table, i.e. one PPI industry classification is now mapped to one or more items in the IO table.[3] For each item j, we can compute the share of imported inputs in the total amount of inputs (both imports and those domestically produced) used for the production of item j:

$$\textit{Imported Input Share}_{j} = \frac{\textit{Imported Input}_{j}}{\textit{Total Input}_{j}}$$

Then, for each sector S, we compute the weighted average of those imported input shares for each item j, where the weight on item j is the total inputs used in the production of item j, divided by the total inputs used in the production of all items in sector S.[4] It is essentially the same as the imported inputs used for the items in Sector S divided by the total inputs (both imported and domestically produced) used for the items in Sector S .

$$\textit{Imported Input Share}_{S} = \sum_{j \in S} \textit{Imported Input Share}_{j} \times \frac{\textit{Total Input}_{j}}{\textit{Total Input}_{S}} = \frac{\sum_{j \in S} \textit{Imported Input}_{j}}{\textit{Total Input}_{S}}$$

$$\textit{Total Input}_{S} = \sum_{j \in S} \textit{Total Input}_{j}$$

[2]This is following Rauch's method. Each commodity's trade share is its imports and exports divided by the sum of total imports and exports of all the commodities in that sector. We implicitly assume that each commodity's importance in a sector is proportional to its trading volume.

[3]The number of items in the IO table are much smaller, i.e. the classification is much broader, so we map each PPI industry classification to one or more IO items rather than the other way around. Some PPI industries are, therefore, matched with the same IO item(s).

[4]Note that item j can be in sector S and S′ at the same time.

For the imported input prices, we use the Imported Price Index from the Bank of Korea. We compute the import price changes between 1996 and 98 for each group of the imported input price indices. We, then, map each item in the IO table to one or more closest groups of the imported input price indices. For each item j in the IO table, we average over price changes across groups of import price indices matched, and denote it as $\Delta p^{\mathtt{import}}_{j,96-98}$. Then, using the IO table for imports and $\Delta p^{\mathtt{import}}_{j,96-98}$, we compute how each item j's imported input price has changed in 1996-98:

$$\Delta \text{Imported Input Price}_{j,96-98} = \sum_{j'} \frac{\text{Imported Input}_{j,j'}}{\text{Imported Input}_j} \Delta p^{\mathtt{import}}_{j',96-98}$$

where Imported $\text{Input}_{j,j'}$ is how much item j' are imported as inputs in the production of item j, and Imported Input_j is the total imported inputs used in producing item j.[5]

Since we have a mapping of a PPI industry classification to items in the IO table, we can compute how the import price of imported input has changed for each sector, S:

$$\Delta \text{Imported Input Price}_{S,96-98} = \sum_{j \in S} \Delta \text{Imported Input Price}_{j,96-98} \times \frac{\text{Imported Input}_j}{\text{Imported Input}_S}$$

$$\text{Imported Input}_S = \sum_{j \in S} \text{Imported Input}_j$$

Price stickiness

We use the median frequency of price changes in Table 12 of Nakamura and Steinsson (2008) to measure price stickiness. We map each PPI industry classification to a broad group over which the price stickiness is measured in Table 12 of Nakamura and Steinsson (2008).[6]

[5] Note that IO table is not in 1996 but in 1995 due to the data availability.

[6] In this mapping, the number of groups in Table 12 is much smaller, so many of PPI industries are matched to the same broad groups, over which the price stickiness is defined.

B.3 Robustness check

Table B.1: Industry price dynamics and short-term FC debt ratio

	(1)	(2)	(3)
ST FC debt ratio	0.481***	0.452**	0.370**
	(0.176)	(0.180)	(0.186)
LT FC debt ratio	0.061	0.059	0.131
	(0.185)	(0.187)	(0.177)
Log change of number of firms		0.151	0.075
		(0.121)	(0.123)
Rauch dummy			-0.045*
			(0.027)
Imported input share			0.131*
			(0.074)
Degree of price stickiness			-0.000
			(0.002)
R^2	0.190	0.197	0.258
N. of cases	157	157	149

B.4 Firm-level regressions: other variables

Table B.2: Firm's performance during the crisis

Δy_{96-98}	(1) Capital growth	(2) MP growth	(3) Employment growth
ST FC	-6.13**	-3.54*	-4.48***
	(3.19)	(2.02)	(0.81)
LT FC	-3.4	-1.5	-1.35*
	(2.3)	(1.7)	(0.8)
Size * ST FC	0.15**	0.205**	0.17***
	(0.12)	(0.07)	(0.03)
Size * LT FC	0.07	0.085	0.05*
	(0.095)	(0.07)	(0.03)
R^2	0.0438	0.1217	0.1150
N	1828	2142	2120

Note: This table shows the results from firm-level regressions. The dependent variables are the change of (1) log capital stock, (2) log labor productivity, and (3) log employment from 1996 to 1998. The main regressors are firm-level short-term foreign currency debt ratio (ST FC) and cross product between size and ST FC in 1996. The size is measured as the log of real assets. To alleviate potential endogeneity issue, we use the pre-crisis (1996) value of regressors. Robust standard errors are calculated in paranthesis. *, **, and *** indicate that the coefficient estimate is significantly different from zero at 10%, 5% and 1% level, respectively.

B.5 Computation - stationary industry equilibrium

Market environment – partial equilibrium

- In the partial equilibrium setting, we normalize aggregate consumption as $Y_t = \bar{Y}$ and aggregate price as P_t=1 (both are given parameters).

- We assume CES-aggregator for aggregate consumption

$$\bar{Y} = \left(\sum_i Y_i^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}, \quad \nu > 1$$

where Y_i is demand for sector i's composite good.

- Given $\bar{Y}$ and $P_t = 1$, we can derive the demand for Y_i as

$$Y_i = P_i^{-\nu}\bar{Y}$$

We first calculate stationary industry equilibrium without any aggregate shocks. Then we impose an unexpected depreciation of exchange rate, i.e. unexpected increase in ξ, and calculate the transition price dynamics.

Step1.

First, we guess the industry price P^0. Then, given the aggregate price P^0, and consumption Y^0, we solve the following firm's problem.

$$v(d,k,a,z) = \max_{c\geqslant 0,d',k',a'} \frac{c^{1-\gamma}}{1-\gamma} + \beta E_{z'}[v(d',k',a',z')]$$

$$\text{s.t. (i) } c+k'-(1-\delta)k+\Phi(k,k')+a'+d\big(\lambda+(1-\lambda)\frac{\xi}{\xi_{-1}}\big) = \pi(k,z)+\frac{d'}{1+r}+w+a$$

$$\text{(ii) } \frac{1}{1+r}d' \leqslant \theta k', \quad \text{(iii) } wn \leqslant a$$

where

$$\Phi(k,k') = \frac{\phi}{2}\Big(\frac{k'-(1-\delta)k}{k}\Big)^2 k$$

$$\text{and} \quad \pi(k,z) = \max_n \; p(y)y - wn$$

$$\text{s.t. i) } y = zk^\alpha n^{1-\alpha}$$

$$\text{ii) } p(y) = exp\left(\frac{1}{\epsilon}\Big(1-\big(\frac{y}{Y^0}\big)^{\epsilon/\sigma}\Big)\right)P^0$$

Then we get a set of policy functions

$$k'(k,d,a,z;P^0),\; d'(k,d,a,z;P^0),\; a'(k,d,a,z;P^0),\; p(k,d,a,z;P^0).$$

To solve the firm's dynamic problem, we used Howard policy iteration method.

Step2.

Given the firm's optimal policy functions

$$k'(k, d, a, z; P^0),\ \ d'(k, d, a, z; P^0),\ \ a'(k, d, a, z; P^0)$$

and the law of motion for idiosyncratic productivity shocks z, we find a stationary distribution

$$\psi(k, d, a, z; P^0).$$

Step3.

Using

$$p(k, d, a, z; P^0)\ and\ \psi(k, d, a, z; P^0)$$

we find

$$\tilde{P} = exp\left(\int ln\Big(p(k, d, a, z; P^0)\Big) d\psi(k, d, a, z; P^0)\right)$$

Then we compare $\tilde{P}$ and P^0. If they are close enough, we are done. Otherwise, we update new guess for aggregate price as

$$P^1 = x\tilde{P} + (1-x)P^0 \quad \text{for some } x\ \in (0, 1)$$

and then restart the loop from Step 1.

B.6 Computation - Transition Dynamics

We assume that in period 0, the economy is in a stationary equilibrium where all firms believe there is no change in future aggregate shocks. However, in period 1, there is a one-time unexpected shocks to exchange rate ξ in the economy. At that point, firms observe complete path of future exchange rates from period 1. It is assumed that the exchange rates stay constant at the new level (period 1 level) so that there is no deviation from UIP. Specifically, we assume that the evolution of the exchange rate is characterized by a sequence $\{\xi_t\}_{t=0}^{\infty}$ such that $\xi_0 = 1$ and $\xi_t = 2.1,$ for $t \geqslant 1$.

Step1.

First, we guess a specific period $\bar{T}$ such that the economy is in a stationary equilibrium from period $T > \bar{T}$ onwards.

Step2.

Then we guess the sequence of industry-level prices $\bar{P}^0 = \{P_t^0\}_{t=0}^{\bar{T}}$ and corresponding output $\bar{Y}^0 = \{Y_t^0\}_{t=0}^{\bar{T}}$.

Step3.

Given the sequences of $\{\xi_t\}_{t=0}^{\infty}$, $\{P_t^0\}_{t=0}^{\bar{T}}$, and $\{Y_t^0\}_{t=0}^{\bar{T}}$, we solve for a sequence of the firm's optimal problem. Specifically, we set $v_{\bar{T}}(d,k,a,z) = v(d,k,a,z)$ where $v(d,k,a,z)$ is the value function we obtain from stationary equilibrium. Then, from $t = \bar{T}$ to $t = 2$, we solve the following firm's problem sequentially

$$v_{t-1}(d,k,a,z) = \max_{c\geqslant 0, d',k',a'} \frac{c^{1-\gamma}}{1-\gamma} + \beta E_{z'}[v_t(d',k',a',z')]$$

s.t. $(i)\ c + k' - (1-\delta)k + \Phi(k,k') + a' + d\big(\lambda + (1-\lambda)\frac{\xi_t}{\xi_{t-1}}\big) = \pi(k,z) + \frac{d'}{1+r} + w + a$

$$(ii)\ \frac{1}{1+r}d' \leqslant \theta k' \quad (iii)\ wn \leqslant a$$

where

$$\Phi(k,k') = \frac{\phi}{2}\big(\frac{k'-(1-\delta)k}{k}\big)^2 k$$

$$\text{and} \quad \pi(k,z) = \max_{n}\ p(y)y - wn$$

$$\text{s.t. i) } y = zk^{\alpha}n^{1-\alpha}$$

$$\text{ii) } p(y) = exp\left(\frac{1}{\epsilon}\left(1 - (\frac{y}{Y_t^0})^{\epsilon/\sigma}\right)\right)P_t^0$$

Then we have

$$k_t(k, d, a, z; \bar{P}^0),\ d_t(k, d, a, z; \bar{P}^0),\ p_t(k, d, z; \bar{P}^0),\ t = 1, ..., \bar{T}$$

.

Step4.

With policy functions in hand, we compute a sequence of distribution starting from $t = 1$

$$\psi_t(k, d, a, z; \bar{P}^0),\ t = 1, ..., \bar{T}$$

and sequence of industry prices as

$$\tilde{P}_t = exp\left(\int ln\Big(p_t(k, d, a, z; \bar{P}^0)\Big)d\psi_t(k, d, a, z; \bar{P}^0)\right)$$

Step5.

Then we compare the original guess $\bar{P}^0$ and new sequence $\tilde{P} = \{\tilde{P}_t\}_{t=1}^{\bar{T}}$. If they are close enough, we move to Step 6. Otherwise, we update new guess for aggregate price as

$$\bar{P}^1 = x\tilde{P} + (1 - x)\bar{P}^0 \quad \text{for some } x\ \in (0, 1)$$

and then restart the loop from Step 2.

Step6.

If the difference between aggregate price at $\bar{T} - 1$ and $\bar{T}$ is small enough, then we are done. Otherwise, we return to Step 1 and reset $\bar{T}$.

Bibliography

Daniel Ackerberg, Kevin Caves, and Garth Frazer. Structural identification of production functions. 2006.

Arip M Affendy, Lau Sim Yee, and Satoru Madono. Commodity-industry classification proxy: A correspondence table between sitc revision 2 and isic revision 3. *Memeo*, 2010.

Ivan Alfaro, Nicholas Bloom, and Xiaoji Lin. The finance uncertainty multiplier. Technical report, National Bureau of Economic Research, 2018.

Heitor Almeida, Chang-Soo Kim, and Hwanki Brian Kim. Internal capital markets in business groups: Evidence from the asian financial crisis. *The Journal of Finance*, 70(6):2539–2586, 2015.

Mary Amiti, Oleg Itskhoki, and Jozef Konings. International shocks, variable markups, and domestic prices. *The Review of Economic Studies*, 2018.

Cristina Arellano, Yan Bai, and Patrick J Kehoe. Financial frictions and fluctuations in volatility. *Journal of Political Economy*, 127(5):2049–2103, 2019.

Rüdiger Bachmann and Christian Bayer. 'wait-and-see'business cycles? *Journal of Monetary Economics*, 60(6):704–719, 2013.

Marvin J Barth and Valerie A Ramey. The cost channel of monetary transmission. *NBER macroeconomics annual*, 16:199–240, 2001.

Randy A Becker, John Haltiwanger, Ron S Jarmin, Shawn D Klimek, and Daniel J Wilson. Micro and macro data integration: The case of capital. In *A new architecture for the US national accounts*, pages 541–610. University of Chicago Press, 2006.

Sreedhar T Bharath and Tyler Shumway. Forecasting default with the merton distance to default model. *The Review of Financial Studies*, 21(3):1339–1369, 2008.

Saki Bigio. Endogenous liquidity and the business cycle. *American Economic Review*, 105(6):1883–1927, 2015.

Nicholas Bloom. The impact of uncertainty shocks. *econometrica*, 77(3):623–685, 2009.

Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry. Really uncertain business cycles. *Econometrica*, 86(3):1031–1065, 2018.

Nick Bloom, Stephen Bond, and John Van Reenen. Uncertainty and investment dynamics. *The review of economic studies*, 74(2):391–415, 2007.

Ricardo J Caballero, Eduardo MRA Engel, John C Haltiwanger, Michael Woodford, and Robert E Hall. Plant-level adjustment and aggregate investment dynamics. *Brookings papers on economic activity*, pages 1–54, 1995.

Dario Caldara, Cristina Fuentes-Albero, Simon Gilchrist, and Egon Zakrajšek. The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88:185–207, 2016.

Guillermo A Calvo and Carmen M Reinhart. Fear of floating. *The Quarterly journal of economics*, 117(2):379–408, 2002.

Luis Felipe Céspedes, Roberto Chang, and Andres Velasco. Balance sheets and exchange rate policy. *American Economic Review*, 94(4):1183–1193, 2004.

Varadarajan V Chari, Lawrence Christiano, and Patrick Kehoe. The gertler-gilchrist evidence on small and large firm sales. *manuscript, January*, 2007.

Yoon Je Cho, Robert N McCauley, et al. Liberalising the capital account without losing balance: lessons from korea. *China's capital account liberalisation: international perspectives, BIS Papers*, (15):75–92, 2003.

Lawrence J Christiano, Roberto Motto, and Massimo Rostagno. Risk shocks. *The American Economic Review*, 104(1):27–65, 2014.

Lawrence J Christiano, Martin S Eichenbaum, and Mathias Trabandt. Understanding the great recession. *American Economic Journal: Macroeconomics*, 7(1): 110–67, 2015.

Russell W Cooper and John C Haltiwanger. On the nature of capital adjustment costs. *The Review of Economic Studies*, 73(3):611–633, 2006.

Nicolas Crouzet and Neil R Mehrotra. Small and large firms over the business cycle. Technical report, 2020.

Jan De Loecker and Frederic Warzynski. Markups and firm-level export status. *American economic review*, 102(6):2437–71, 2012.

Ryan A Decker, Pablo N D'Erasmo, and Hernan Moscoso Boedo. Market exposure and endogenous firm volatility over the business cycle. *American Economic Journal: Macroeconomics*, 8(1):148–98, 2016.

Marco Del Negro, Marc P Giannoni, and Frank Schorfheide. Inflation in the great recession and new keynesian models. *American Economic Journal: Macroeconomics*, 7(1):168–96, 2015.

Mark Doms, Timothy Dunne, et al. Capital adjustment patterns in manufacturing plants. *Review of economic dynamics*, 1(2):409–429, 1998.

Mark Gertler and Simon Gilchrist. Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics*, 109 (2):309–340, 1994.

Vivek Ghosal and Prakash Loungani. The differential impact of uncertainty on investment in small and large businesses. *The Review of Economics and Statistics*, 82(2):338–343, 2000.

Vivek Ghosal and Yang Ye. Uncertainty and the employment dynamics of small and large businesses. *Small Business Economics*, 44(3):529–558, 2015.

Simon Gilchrist and Jae W Sim. Investment during the korean financial crisis: a structural econometric analysis. Technical report, National Bureau of Economic Research, 2007.

Simon Gilchrist, Jae W Sim, and Egon Zakrajšek. Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research, 2014.

Simon Gilchrist, Raphael Schoenle, Jae Sim, and Egon Zakrajšek. Inflation dynamics during the financial crisis. *American Economic Review*, 107(3):785–823, 2017.

Xavier Giroud and Holger M Mueller. Capital and labor reallocation within firms. *The Journal of Finance*, 70(4):1767–1804, 2015.

Joao F Gomes. Financing investment. *American Economic Review*, 91(5):1263–1285, 2001.

Gita Gopinath and Oleg Itskhoki. Frequency of price adjustment and pass-through. *The Quarterly Journal of Economics*, 125(2):675–727, 2010.

Francois Gourio and Anil K Kashyap. Investment spikes: New facts and a general equilibrium exploration. *Journal of Monetary Economics*, 54:1–22, 2007.

Bryan Gutierrez, Victoria Ivashina, and Juliana Salomao. Why is dollar debt cheaper? evidence from peru. *Evidence from Peru (May 10, 2020)*, 2020.

Priit Jeenas. Firm balance sheet liquidity, monetary policy shocks, and investment dynamics. In *Technical Report*. Working paper, 2018.

Matthias Kehrig and Nicolas Vincent. Good dispersion, bad dispersion. Technical report, National Bureau of Economic Research, 2019.

Hye-ran Kim. A studyontheconstructionofintegrated a study on the construction of integrated economical classification framework. *Memeo*, 2008.

Yun Jung Kim, Linda L Tesar, and Jing Zhang. The impact of foreign liabilities on small firms: Firm-level evidence from the korean crisis. *Journal of International Economics*, 97(2):209–230, 2015.

Miles S Kimball. The quantitative analytics of the basic neomonetarist model. Technical report, National Bureau of Economic Research, 1995.

Yann Koby and Christian K Wolf. Aggregation in heterogeneous-firm models: Theory and measurement. 2020.

David Kohn, Fernando Leibovici, and Michal Szkup. Financial frictions and export dynamics in large devaluations. *Available at SSRN 2654868*, 2018.

Paul Krugman. Balance sheets, the transfer problem, and financial crises. In *International finance and financial crises*, pages 31–55. Springer, 1999.

Per Krusell and Anthony A Smith, Jr. Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy*, 106(5):867–896, 1998.

Marianna Kudlyak and Juan M Sanchez. Revisiting the behavior of small and large firms during the 2008 financial crisis. *Journal of Economic Dynamics and Control*, 77:48–69, 2017.

John V Leahy and Toni M Whited. The effect of uncertainty on investment: Some stylized facts. Technical report, National Bureau of Economic Research, 1995.

Gregor Matvos and Amit Seru. Resource allocation within firms and financial market dislocation: Evidence from diversified conglomerates. *The Review of Financial Studies*, 27(4):1143–1189, 2014.

Emi Nakamura and Jón Steinsson. Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics*, 123(4):1415–1464, 2008.

Pablo Ottonello and Thomas Winberry. Financial heterogeneity and the investment channel of monetary policy. Technical report, National Bureau of Economic Research, 2020.

James E Rauch. Networks versus markets in international trade. *Journal of international Economics*, 48(1):7–35, 1999.

Juliana Salomao and Liliana Varela. Exchange rate exposure and firm dynamics. 2018.

Georg Strasser. Exchange rate pass-through and credit constraints. *Journal of Monetary Economics*, 60(1):25–38, 2013.

George Tauchen. Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters*, 20(2):177–181, 1986.

Martin Uribe and Vivian Z Yue. Country spreads and emerging countries: Who drives whom? *Journal of international Economics*, 69(1):6–36, 2006.

Cutler Wilmer and Hale Pickering. D. llp,"2017 ipo report,". Technical report, Technical report, 2017.

Thomas Winberry. Lumpy investment, business cycles, and stimulus policy. 2020.

Jiao Yang, Ohyun Kwon, Jae-Whak Roh, et al. International trade and the currency composition of corporate debt. Technical report, LeBow College of Business, Drexel University, 2021.