ABSTRACT

Title of dissertation: ESSAYS ON MACROECONOMICS AND CORPORATE FINANCING DECISIONS

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This thesis comprises two studies in the relationship between corporate firms' financing decisions and business cycles. In the first chapter, I propose a transmission mechanism linking uncertainty shocks to macroeconomic variables through firms' financing decisions, with an emphasis on the role of equity financing. When uncertainty is high, equity issuance is limited, as firms are less likely to generate positive profits, and are more tempted to divert profits. As a result, external equity financing shrinks, and this generates additional amplification since total equity financing decreases. Based on this mechanism, I address two questions. First, how are equity financing decisions and associated agency costs affected by uncertainty shocks, and how does equity amplify the response of macroeconomic variables to uncertainty shocks? I build a DSGE financial accelerator model with both debt and equity financing that generates amplification of macroeconomic variables in response to uncertainty shocks. The troughs of macroeconomic variables generated by my model are approximately 30 percent deeper compared to a standard model with only a debt contract. The amplification allows the model to predict procyclical debt

and equity financing, and countercyclical external financing costs, a combination which existing models are unable to explain. Second, how does uncertainty affect corporate firms' equity financing decisions empirically? Using balance sheet data of U.S. listed firms from 1993 to 2014, I find that a one standard deviation increase in the level of uncertainty is associated with a 0.7 percentage point decrease in the ratio of equity financing to total assets.

In the second chapter, we study the influence of external financial factors on economic activity in emerging economies (EMEs), motivated by a considerable increase in foreign financing by the corporate sector in EMEs since the early 2000s, mainly in the form of bond issuance. We build a quarterly external financial indicator for several EMEs using bond-level data on spreads of corporate bonds issued in foreign capital markets, and examine its relationship with economic activity. Results show that this indicator has considerable predictive power for future economic activity. Furthermore, an identified adverse shock to the financial indicator generates a large and protracted fall of real output growth. About a third of the forecast error variance for output is associated with this shock. These findings are robust to controlling for possible spillovers from sovereign to corporate risk, among other considerations.

ESSAYS ON MACROECONOMICS AND CORPORATE FINANCING DECISIONS

by

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Dedication

To my parents and my sister.

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Disclaimer

Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent.

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List of Abbreviations

AR	Autoregressive
BIS	Bank for International Settlements
bp	Basis Point
CBOE	Chicago Board Options Exchange
CRSP	Center for Research in Security Prices
CSV	Costly State Verification
DSGE	Dynamic Stochastic General Equilibrium
EFI	External Financial Indicator
EMBI	Emerging Markets Bond Index
EME	Emerging Economies
FEVD	Forecast Error Variance Decomposition
FRED	Federal Reserve Economic Data
GDP	Gross Domestic Product
IDB	Inter-American Development Bank
IDS	International Debt Security
IMF	International Monetary Fund
IRF	Impulse-Response Function
ISIN	International Securities Identification Number
LSDV	Least Square Dummy Variable
NAICS	North American Industry Classification System
NBER	National Bureau of Economic Research
NFC	Non-Financial Corporations
OAS	Option-Adjusted Spread
RBC	Real Business Cycle
SD	Standard Deviation
SEO	Seasoned Equity Offerings
SVAR	Structural Vector Autoregressive
TFP	Total Factor Productivity
TFPR	Revenue-Based Productivity
VECM	Vector Error Correction Model
VIX	CBOE Volatility Index

Chapter 1: Uncertainty Shocks, Equity Financing, and Business Cycle Amplifications

1.1 Introduction

I develop a dynamic stochastic general equilibrium model where uncertainty shocks are amplified through equity financing frictions. The key prediction of the model is procyclical debt and equity issuance driven by countercyclical costs of debt and equity financing. The model introduces a new transmission mechanism through which uncertainty shocks affect firms' external financing decisions and macroeconomic variables. The financial frictions that arise from equity contracts play a central role in the proposed transmission mechanism. The notion of uncertainty is defined as time-varying dispersion of idiosyncratic productivity across firms (Bloom et al., 2012, Christiano et al., 2014).

In the model, agency problems between entrepreneurs and external shareholders worsen when uncertainty increases. During uncertain times, entrepreneurs are more likely to default and less likely to generate positive profits as lower-tail risk increases. At the same time, entrepreneurs are more tempted to divert profits from external shareholders as upper-tail risk increases. As a result, the agency problem worsens and external shareholders find investing in equity less attractive when uncertainty is high. This limits entrepreneurs' external equity financing as the cost of equity financing increases. Limited equity financing has a direct effect on the size of the balance sheet by reducing total equity. As a consequence, entrepreneurs operate at a smaller size, and a recession ensues.

Based on this mechanism, I answer two research questions. On the theoretical front, I study how equity financing decisions and associated agency costs are affected by uncertainty shocks, and in turn, how equity frictions amplify the response of macroeconomic variables to uncertainty shocks. In particular, I develop a small-scale DSGE financial accelerator model that introduces financial frictions in equity contracts to a standard debt-only model (Carlstrom and Fuerst, 1997). In response to a one standard deviation increase in uncertainty, debt and equity financing decrease from the steady state by approximately 2% and 4% respectively. As firms scale down, aggregate output and investment decrease by approximately 0.4% and 3%, respectively. The troughs of variables in response to uncertainty shocks are approximately 30% deeper than in a standard financial accelerator model with only a debt contract.

The amplification of uncertainty shocks in the model has an important implication for the cyclical properties of debt and equity along with the costs of external financing. In particular, the model simulation generates procyclical debt and equity issuance (Covas and Den Haan, 2011), along with countercyclical costs of debt and equity financing, all of which are consistent with empirical observations. In contrast, existing models are unable explain the coexistence of procyclical debt and equity financing and countercyclical external financing costs. For example, Jermann and Quadrini (2012) build a general equilibrium model to investigate the effect of financial shocks, but their model predicts countercyclical equity financing, which is inconsistent with firm-level evidence reported by Covas and Den Haan (2011). Covas and Den Haan (2012) build a partial equilibrium model to explain procyclical equity financing. However, their model cannot explain the coexistence of procyclical equity financing and countercyclical costs of external financing unless they introduce an ad-hoc assumption on countercyclical costs of equity financing.

The model's key innovation is its explicit modeling of both debt and equity financing decisions. I assume information asymmetry between entrepreneurs and external shareholders, in addition to costly state verification (CSV) (Townsend, 1979), which is a standard debt financing friction. I introduce equity financing frictions following La Porta et al. (2002) and Levy and Hennessy (2007). In particular, I assume that the realization of productivity is entrepreneurs' private information, and entrepreneurs can divert profits from external shareholders by misreporting profits. However, to do so they must sacrifice resources proportional to the size of the balance sheet.

In this environment, entrepreneurs divert profits if and only if realized productivity is sufficiently high so that the size of diverted profits is greater than the cost of diversion. As a result, as upper-tail risk increases, the more entrepreneurs are tempted to divert profits. Since external shareholders internalize the increased probability of profit diversion, equity financing becomes more costly to entrepreneurs as upper-tail risk increases, which limits the amount of equity financing. Equity financing is also limited when lower-tail risk increases, because entrepreneurs less likely to generate positive profits, so that external shareholders find investing in equity less attractive. A symmetric increase in uncertainty implies increases in both lower- and upper-tail risk. For this reason, the model predicts a decrease in equity financing and an increase in costs of external financing when uncertainty is high.

Within this framework, the response of macroeconomic variables to uncertainty shocks is amplified relative to a model with only debt finance. When uncertainty is high, external equity financing is limited and, in turn, total equity shrinks. This affects the size of the balance sheet both directly and indirectly, as debt financing is further limited, since total equity determines the amount of debt that entrepreneurs can raise.

On the empirical front, I study how firms' equity financing decisions are related to the level of uncertainty, using balance sheet data of U.S. listed firms from annual Compustat for the sample period 1993-2014. Following a panel regression approach suggested by Covas and Den Haan (2011), I find that a one standard deviation increase in the level of uncertainty is associated with a 0.7 percentage point decrease in the ratio of equity financing to total assets, where I measure uncertainty as time-varying dispersion of shocks to firm-level total factor productivity.

In the next section, I discuss related literature and how my work contributes. In Section 1.3, I introduce debt and equity contracts in a partial equilibrium setting. In Section 1.4, I embed the partial equilibrium financial contract into a DSGE model. Section 1.5 presents numerical results of the DSGE model. Section 1.6 presents empirical evidence on the cyclicality of equity financing in the context of uncertainty shocks. The final section concludes.

1.2 Literature Review

A wide literature has examined the potential importance of uncertainty shocks as a driver of U.S. business cycles. Among the various channels through which uncertainty affects the macroeconomy, many studies highlight the role of financial frictions. However, these studies mainly focus on debt contracts, and abstract from equity financing frictions.

In contrast, there is a long tradition in the corporate finance literature in which equity financing is not simply a sideshow, for example Myers and Majluf (1984). This literature departs from Modigliani and Miller (1958), in that firms' choice between debt and equity financing has real implications, because it affects the firms' investment decisions.

My research contributes to both strands of the literature. First, I contribute to the literature that studies how uncertainty shocks are transmitted to the economy. Bloom (2009) finds that uncertainty shocks can generate a recession, as firms delay investment until uncertainty is resolved. While Bloom (2009) highlights the "wait-and-see" channel, another line of literature investigates the transmission of uncertainty shocks through financial frictions. For example, Gilchrist et al. (2014) provide evidence that debt frictions play a substantial role in the transmission of uncertainty shocks, and build a DSGE model that is consistent with their empirical findings. In a similar vein, Christiano et al. (2014) estimate a large-scale financial accelerator model with debt contracts and idiosyncratic uncertainty shocks and confirm the significant role of uncertainty shocks in the U.S. business cycle.[1] In this class of models, the default rate increases as uncertainty increases. As a result, debt financing is limited and firms become smaller. Through this channel, adverse uncertainty shocks generate recessions.

However, these studies typically abstract from equity financing. I add to the literature by embedding both debt and equity contracts into the model. Allowing for equity contracts is important, as my model generates a larger amplification of macroeconomic variables to uncertainty shocks compared to models with only debt contracts.

Secondly, I contribute to the literature on the cyclicality of debt and equity financing. For example, Jermann and Quadrini (2006, 2012) document countercyclical equity financing using Flow of Funds Accounts of the Federal Reserve Board, and build a model with both debt and equity financing to study how financial shocks generate business cycles. Their model predicts countercyclical equity financing, which is inconsistent with studies of firm-level data such as Covas and Den Haan (2011, 2012). The latter document that both debt and equity financing are procyclical for listed U.S. firms in all size classes except for the top 1% firms by asset size, where smaller firms have stronger procyclicality. Covas and Den Haan (2012) develop a partial equilibrium model in which firms finance investment with both debt and equity. In their model, firms scale up their business in response to positive produc-

[1]Similarly Cesa-Bianchi and Fernandez-Corugedo (2015) build a DSGE model with both macro-level uncertainty (time-varying second moment of TFP shocks) and micro-level uncertainty (time-varying dispersion of idiosyncratic productivity) and show that micro-level uncertainty shocks generate a recession through financial market frictions.

tivity shocks. However, since debt financing increases the likelihood of default, firms have an incentive to issue equity to avoid excessive leverage when they issue debt.[2] Although their model predicts both procyclical debt and equity financing, it fails to predict countercyclical real borrowing costs and a countercyclical default rate unless countercyclical equity financing costs are assumed. They introduce countercyclical equity financing costs into the model by simply assuming an ad-hoc functional relationship between productivity and equity financing costs without a microfoundation.

In contrast, my framework predicts procyclical debt and equity financing along with endogenous countercyclical external financing costs, all of which are consistent with the data. Under the CSV framework, agency costs decrease when the level of TFP decreases since firms scale down and need less external financing. While adverse uncertainty shocks partly offset this effect by increasing agency costs, the effect of adverse uncertainty shocks is not large enough to generate countercyclical agency costs, if only a debt contract is considered. However, in my model with both debt and equity contracts, the effect of uncertainty shocks on the cyclicality of financing frictions dominates the effect of TFP level shocks, as equity financing frictions amplify uncertainty shocks. So, the model is able to generate both procyclical debt and equity financing, a countercyclical default rate and countercyclical cost of debt and equity finance.

[2] Begenau and Salomao (2015) build a heterogenous agent general equilibrium model to simultaneously explain procyclical equity financing of small firms and coutercyclicality of the largest firms. Small firms issue debt and equity procyclically for a similar reason as in Covas and Den Haan (2012). However, the largest firms find debt financing much cheaper during the expansion, since they are already close to the efficient scale of production, and thus the impact of having an additional unit of debt on the default probability is low. As a result, they replace equity with debt during expansions to take an advantage of a tax benefit on debt over equity.

My empirical finding that equity financing is negatively correlated with uncertainty is related to existing empirical studies of the patterns and cyclicality of debt and equity financing. Fama and French (2005) document that equity financing is common among listed firms in the U.S. Covas and Den Haan (2011, 2012) show that both debt and equity financing are procyclical for listed U.S. firms in all size classes except for the top 1% of firms by asset size, where smaller firms have stronger procyclicality. Erel et al. (2012) document a similar pattern. They find that seasoned equity offerings (SEO) decrease during NBER-defined recessions, which is a pattern largely driven by noninvestment-grade firms. They also find that bond financing is procyclical, which is also largely driven by noninvestment-grade firms. I add to this literature by investigating cyclical patterns of debt and equity finance in response to changes in uncertainty. I provide empirical evidence that debt and equity financing decreases during periods of high uncertainty, and build a DSGE model that is consistent with empirical evidence.

1.3 Financial Contracts

In this section, I build a theoretical model with both debt and equity contracts that predicts a decrease in debt and equity financing in response to increased uncertainty. I first discuss the financial contract among entrepreneurs, lenders, and external shareholders in a partial equilibrium setting. The partial equilibrium analysis will be extended to a dynamic stochastic general equilibrium model in Section 1.4.

I model the debt contract as in Carlstrom and Fuerst (1997), who introduce debt financing frictions into a computationally tractable general equilibrium model. The main friction in the debt contract arises from an information asymmetry between lenders and borrowers. Following Townsend (1979), lenders must pay a monitoring cost in order to verify the true productivity of borrowers (Costly State Verification, CSV). However their model abstracts from equity financing. I introduce equity financing frictions into Carlstrom and Fuerst (1997) by assuming that entrepreneurs can divert profits at some cost, following La Porta et al. (2002) and Levy and Hennessy (2007).

Three types of agents participate in the financial contract: entrepreneurs, lenders, and external shareholders. I assume that all contract parties are risk neutral, and only care about expected returns. Entrepreneurs, who operate capital good producing firms, have access to a stochastic constant-returns-to-scale capital production technology which transforms consumption goods into capital goods. Entrepreneurs finance their investment projects prior to the realization of idiosyncratic productivity shocks using debt and external equity, along with internal equity. Most of the financial accelerator literature abstracts from external equity and uses the term 'net worth' to refer to both total equity and internal equity. However, there is a clear distinction between internal and external equity in this paper. To avoid confusion, I use the term internal equity instead of net worth to refer to the funds that entrepreneurs put into the contract. After the realization of idiosyncratic productivity, entrepreneurs can potentially either default on debt or divert profits. In case of debt default, lenders pay a monitoring cost to verify the realized idiosyncratic shock and take all the output from entrepreneurs. In case of profit diversion, entrepreneurs first repay principal and interest on debt. However, instead of paying all remaining profits to external shareholders, entrepreneurs take a fraction of the profit which should belong to external shareholders. To divert profits entrepreneurs must sacrifice a certain amount of capital goods, which is proportional to the size of the balance sheet.

There are two sources of aggregate risk in the economy: total factor productivity (TFP) shocks, and uncertainty shocks. TPF shocks are standard as in real business cycle models. Uncertainty shocks refer to a stochastic time-varying dispersion of idiosyncratic productivity shocks. Aggregate shocks are realized at the beginning of the period. All financial contracts are intra-temporal, and thus there is no aggregate shock realized for the duration of the contract. As a result all parties take the dispersion of idiosyncratic productivity shocks parametrically. This assumption further allows us to analyze the model first in partial equilibrium, and then in a dynamic general equilibrium setting.

Lenders and external shareholders can be thought of as financial institutions that channel funds from households (which I will discuss when I describe the DSGE model) to entrepreneurs who produce capital goods. The economy is populated with numerous infinitesimal lenders and external shareholders that specialize either in debt or equity. Each financial institution pools deposits from households and lends to or buys shares of numerous infinitesimal entrepreneurs. This allows financial institutions to diversify idiosyncratic risks, and guarantee a fixed return to households.

1.3.1 Setup of Debt and Equity Contracts

I now, analyze debt and equity contracts in a partial equilibrium setting. An entrepreneur i has access to a stochastic constant returns to scale technology $\omega_i i_i$, which transforms i_i units of consumption goods into $\omega_i i_i$ units of capital goods, taking the price of capital q as given.[3] The consumption good is the numeraire, and the price of capital will be endogenously determined in general equilibrium. ω_i denotes an idiosyncratic productivity shock whose distribution is $\ln(\omega_i) \sim N(-\frac{\sigma_\omega^2}{2}, \sigma_\omega^2)$.[4] Idiosyncratic productivity shocks are independently and identically distributed across entrepreneurs in each period. $\phi(\omega)$ and $\Phi(\omega)$ denote the p.d.f and c.d.f of ω_i respectively. The modeling of uncertainty closely follows Christiano et al. (2014). Uncertainty shocks are embedded into the model by assuming that the dispersion of idiosyncratic productivity shocks σ_ω is a time-varying stochastic variable. However, σ_ω does not vary within the duration of financial contracts. For this reason, contract participants take σ_ω parametrically in a partial equilibrium setting. Since contracts are intra-period, I suppress time subscript t for notational simplicity.

An entrepreneur has three different sources for financing their investment project i_i. The investment project requires consumption goods. The first option is to finance with internal equity n_i. For now, I assume that n_i is exogenously fixed for the duration of the contract. In general equilibrium, n_i is determined endogenously as a result of entrepreneurs' capital accumulation decisions. The second

[3] From now on, I use entrepreneurs and capital good producing firms interchangeably depending on context.

[4] This implies $E(\omega_i) = 1$.

option is to issue debt securities $d_i = i_i - e_i - n_i$, where e_i denotes the third source of financing, which is external equity. The size of the project i_i also represents the size of the balance sheet of a capital good producing firm, which consists of debt and total equity, the latter of which in turn is a sum of internal and external equity.[5]

I limit my interest to the case where the optimal size of project i_i is greater than internal equity n_i so that all firms must rely on external financing to some degree. Entrepreneurs borrow d_i before idiosyncratic productivity is realized and promise to return $(1 + r_d)d_i$ units of capital goods to lenders once idiosyncratic productivity is realized and production is taken. After they observe the realization of idiosyncratic productivity, capital good producing firms can default on debt. The realization of idiosyncratic productivity is the entrepreneur's private information. Due to the information asymmetry between lenders and borrowers, lenders have to sacrifice μi_i units of capital goods to verify the firm's reports in case of default. This is a CSV framework as in Carlstrom and Fuerst (1997). After lenders pay the monitoring cost, they seize $\omega_i i_i$, which will in equilibrium be less than the sum of principal and interest.

The other source of external financing is outside equity e_i raised from external shareholders. Entrepreneurs raise equity before the realization of idiosyncratic productivity, and promise to return the fraction $s_i \in [0, 1]$ of the profit (in capital good units) to shareholders as dividends once idiosyncratic productivity is realized. However entrepreneurs can divert profits at a cost proportional to the size of the

[5] From now on, I use the size of the project and the size of the balance sheet interchangeably depending on context.

balance sheet, γi_i. The greater is γ, the more costly it is for entrepreneurs to divert profits since they sacrifice a larger fraction of their balance sheet in case of diversion. Thus, a higher γ represents an economy with better outside investor protection. If profit diversion occurs, entrepreneurs repay their debt to lenders and take a fraction ϕ of the portion of profits promised to shareholders, plus all of the profits promised to themselves, net of diversion costs. ϕ is parametrically given and measures the degree of investor protection together with γ. The higher is ϕ, the more entrepreneurs can divert from external shareholders as the degree of investor protection is low. The return to entrepreneurs under diversion thus equals $(1 - s_i)\left[\omega_i i_i - (1 + r_d)d_i\right] + \phi s_i \left[\omega_i i_i - (1 + r_d)d_i\right] - \gamma i_i$. Note that due to the information asymmetry, external shareholders cannot verify the realized value of idiosyncratic productivity. By assumption, they do not have access to a CSV technology. The friction embedded in the equity contract is taken from La Porta et al. (2002) and Levy and Hennessy (2007). In practice, profit diversion can occur in various forms both legally and illegally. For example, entrepreneurs might reward themselves with excessively large salaries, or install unqualified family members in managerial positions. They could also divert profits by benefiting outside entities controlled by the entrepreneurs, for example, by providing better terms of contract or by transferring assets. In the worst case, entrepreneurs can simply steal profits. In this regard, entrepreneurs in my model represent any type of manager, controlling shareholder, and/or board member who owns a share of the firm's assets, and at the same time actively engages in the firm's managerial decisions. See Johnson et al. (2000) and La Porta et al. (2000) for an extensive list of profit diversions that could occur in practice.

Lastly, note that financing decisions are made prior to the realization of idiosyncratic productivity shocks. As a result, adverse selection is not present in this environment. For example, it will not be the case that firms intending to divert funds are the only firms active in the equity market.

1.3.2 Debt Default and Asset Diversion Thresholds

The next step is to find the productivity thresholds for default and diversion. Entrepreneurs default on debt only if they cannot repay promised returns to lenders. There is no incentive to default when realized output is greater than the sum of the principal and interest, because lenders can recoup their claims in this case. Therefore firms default if and only if the realized shock ω_i satisfies $\omega_i i_i < (1+r_d)d_i$. Thus, the debt default threshold $\bar{\omega}_i$ is defined as

$$\begin{aligned}\bar{\omega}_i &\equiv \frac{(1+r_d)d_i}{i_i} \\ &= \frac{(1+r_d)(i_i - e_i - n_i)}{i_i}\end{aligned}$$

For any given level of external equity e_i and internal equity n_i, once capital good producing firms decide on the debt default threshold $\bar{\omega}_i$ and the size of project i_i, the corresponding interest rate r_d is determined by $(1+r_d) = \frac{\bar{\omega}_i i_i}{(i_i - e_i - n_i)}$. Also note that the share s_i of profits promised to external shareholders does not affect the properties of the debt contract, because shares are residual claims.

Meanwhile entrepreneurs divert profits if and only if the payoff from diversion is greater than the payoff from honoring the equity contract. Therefore entrepreneurs divert profits when the realized shock satisfies

$$\begin{aligned}(1-s_i)\left[\omega_i i_i-(1+r_d)d_i\right] \quad < \quad & (1-s_i)\left[\omega_i i_i-(1+r_d)d_i\right] \\ & +\phi s_i\left[\omega_i i_i-(1+r_d)d_i)\right]-\gamma i_i.\end{aligned}$$

The right-hand side of the inequality denotes the payoff in case of diversion while the left-hand side denotes the payoff in case of honoring the equity contract. By replacing $(1+r_d)d_i$ on both sides with $\bar{\omega}_i i_i$, as derived, this inequality simplifies to

$$\omega_i > \bar{\omega}_i + \frac{\gamma}{\phi s_i}.$$

The right-hand side of this inequality defines the profit diversion threshold productivity $\widehat{\omega}_i \equiv \bar{\omega}_i + \frac{\gamma}{\phi s_i}$. Entrepreneurs divert profits when the realized shock is above $\widehat{\omega}_i$. First, note that $\widehat{\omega}_i$ is an increasing function of γ, the diversion cost, and a decreasing function of ϕ, the share of profits the firm can divert. These results are straight forward. Also, $\widehat{\omega}_i$ is increasing in the fraction of external shares, s_i. A higher fraction of external shares implies that entrepreneurs are only entitled to a small fraction of the profit. In such case, entrepreneurs are more willing to engage in diversion so that they can seize the portion that otherwise belongs to the external shareholders. Second, profit diversion occurs only when the realization of ω_i is sufficiently large. This result is intuitive, since profit diversion is not optimal if entrepreneurs receive nothing after paying the cost of diversion. This result is consistent with Levy and

Hennessy (2007), whose model predicts a stronger incentive for diversion when the realized profits are sufficiently large. Third, the ratio between γ and ϕ (along with s_i) is sufficient to determine the profit diversion threshold. Considering that both parameters measure the degree of investor protection, having both parameters separately might seem redundant. However, each parameter plays a unique role in the model. γ affects the amount of deadweight loss due to diversion, and directly affects entrepreneurs' payoff. Meanwhile, external shareholders' payoff is directly affected by the level of ϕ. Finally, note that $\widehat{\omega}_i > \bar{\omega}_i$. This implies capital good producing firms do not have any incentive to default when they conduct diversion. This is obvious because if there is no profit, there are no resources to divide.

1.3.3 Equilibrium Contract

Since entrepreneurs, lenders, and shareholders are risk neutral during the financial contract period, the expected payoff is the only concern to each party. In this environment, entrepreneurs will choose ($\bar{\omega}_i$, i_i, e_i, s_i) so that their expected payoff is maximized, subject to both lenders and shareholders earning an expected gross return of one. Considering that the financial contracts are intra-period, an expected gross return of one is sufficient to ensure lenders' and external shareholders' participation.

Entrepreneurs' expected payoff from participating in the contract is

$$
\begin{aligned}
\textit{Expected Payoff (entrepreneur)} &= \int_{\bar{\omega}}^{\widehat{\omega}} (1-s)\left[\omega i-(1+r_d)(i-e-n)\right]\Phi(d\omega) \\
&\quad+\int_{\widehat{\omega}}^{\infty}\{(1-s)\left[\omega i-(1+r_d)(i-e-n)\right] \\
&\quad+\phi s\left[\omega i-(1+r_d)(i-e-n)\right]-\gamma i\}\Phi(d\omega) \\
&= \int_{\bar{\omega}}^{\infty}(1-s)\left[\omega i-\bar{\omega} i\right]\Phi(d\omega)+\int_{\widehat{\omega}}^{\infty}\{\phi s\left[\omega i-\bar{\omega} i\right]-\gamma i\}\Phi(d\omega) \\
&= i\left[\int_{\bar{\omega}}^{\infty}(1-s)\left[\omega-\bar{\omega}\right]\Phi(d\omega)+\int_{\widehat{\omega}}^{\infty}\{\phi s\left[\omega-\bar{\omega}\right]-\gamma\}\Phi(d\omega)\right] \\
&= i\times A(\bar{\omega},\, s)
\end{aligned}
$$

where $A(\bar{\omega},\, s) \equiv \int_{\bar{\omega}}^{\infty}(1-s)(\omega-\bar{\omega})\Phi(d\omega)+\int_{\bar{\omega}+\frac{\gamma}{\phi s}}^{\infty}(\omega-\bar{\omega}-\gamma)\,\Phi(d\omega)$ denotes the expected share of output (in terms of capital good units) paid to entrepreneurs.[6] The first term of the first line of the equation denotes entrepreneurs' expected payoff when paying dividends to external shareholders truthfully, while the second and the third terms show the expected payoff to entrepreneurs in case of profit diversion.

The expected payoff to lenders is

$$
\begin{aligned}
\textit{Expected Payoff (lender)} &= \int_0^{\bar{\omega}} \omega i\Phi(d\omega)-\Phi(\bar{\omega})\mu i+\left[1-\Phi(\bar{\omega})\right](1+r_d)(i-e-n) \\
&= \int_0^{\bar{\omega}} \omega i\Phi(d\omega)-\Phi(\bar{\omega})\mu i+\left[1-\Phi(\bar{\omega})\right]\bar{\omega} i \\
&= i\left[\int_0^{\bar{\omega}} \omega\Phi(d\omega)-\Phi(\bar{\omega})\mu+\left[1-\Phi(\bar{\omega})\right]\bar{\omega}\right] \\
&= i\times B(\bar{\omega},\, s)
\end{aligned}
$$

where $B(\bar{\omega},\, s) \equiv \int_0^{\bar{\omega}}\omega\Phi(d\omega)-\Phi(\bar{\omega})\mu+\left[1-\Phi(\bar{\omega})\right]\bar{\omega}$ denotes the expected share

[6] I drop subscript i for notational simplicity.

of output (in terms of capital good units) paid to lenders. The first two terms of the first line of the equation denote lenders' expected payoff when firms default on debt while the last term shows the payoff when firms experience sufficiently large productivity that they repay lenders in full. Note that equity share s is not present in the expression $B(\bar{\omega}, s)$. Since lenders are always repaid with highest priority, s does not directly affect the share of output that lenders will receive. However, s does affect the expected share of output paid to lenders indirectly, since there is an interdependence between $\bar{\omega}$ and s.

Similarly, external shareholders' expected payoff is

$$\begin{aligned}
\textit{Expected Payoff (shareholder)} &= \int_{\bar{\omega}}^{\infty} s\left[\omega i - (1+r_d)(i-e-n)\right]\Phi(d\omega) \\
&\quad - \int_{\widehat{\omega}}^{\infty} \phi s\left[\omega i - (1+r_d)(i-e-n)\right]\Phi(d\omega) \\
&= \int_{\bar{\omega}}^{\infty} s\left[\omega i - \bar{\omega} i\right]\Phi(d\omega) - \int_{\widehat{\omega}}^{\infty} \phi s\left[\omega i - \bar{\omega} i\right]\Phi(d\omega) \\
&= i\left[\int_{\bar{\omega}}^{\infty} s\left[\omega - \bar{\omega}\right]\Phi(d\omega) - \int_{\widehat{\omega}}^{\infty} \phi s\left[\omega - \bar{\omega}\right]\Phi(d\omega)\right] \\
&= i \times C(\bar{\omega}, s)
\end{aligned}$$

where $C(\bar{\omega}, s) \equiv \int_{\bar{\omega}}^{\infty} s\left[\omega - \bar{\omega}\right]\Phi(d\omega) - \int_{\bar{\omega}+\frac{\gamma}{\phi s}}^{\infty} \phi s\left[\omega - \bar{\omega}\right]\Phi(d\omega)$ denotes the expected share of output (in terms of capital good units) paid to shareholders.

The sum of the expected shares paid to each party is given by

$$\begin{aligned}
A+B+C &= \int_{0}^{\infty} \omega\Phi(d\omega) - \Phi(\bar{\omega})\mu - \left[1 - \Phi\left(\bar{\omega} + \frac{\gamma}{\phi s}\right)\right]\gamma \\
&= 1 - \Phi(\bar{\omega})\mu - \left[1 - \Phi\left(\bar{\omega} + \frac{\gamma}{\phi s}\right)\right]\gamma
\end{aligned}$$

where the second term denotes the expected loss due to the monitoring cost, and the third term denotes the expected loss due to the diversion cost. Note that the expected shares paid to each party do not add up to 1, because output may be lost due to costly monitoring or diversion.

Given these expressions for the expected payoffs to each party, the contract problem is defined as

$$\max_{\bar{\omega},s,i,e} qiA(\bar{\omega},s) \quad \textit{subject to} \quad qiB(\bar{\omega},s) \geqq i-e-n$$
$$qiC(\bar{\omega},s) \geqq e$$

where q is the price of capital goods. Entrepreneurs maximize their expected payoff in consumption goods units by optimally choosing ($\bar{\omega}$, s, i, e). The entrepreneurs' objective function is expressed in terms of consumption goods, since entrepreneurs utility depends on consumption in the general equilibrium model presented in Section 1.4. Furthermore lenders participate in the contract only if they recoup the resources they lend in expectation, and external shareholders accept the equity contract only if they receive expected returns at least as large as the amount of external equity they provide to entrepreneurs. Note that the price of capital good q appears on the left-hand side of both constraints but not on the right-hand side, since both debt and equity are raised in consumption goods, and entrepreneurs pay back in capital goods. Obviously both constraints bind with equality at an optimum. From entrepreneurs' perspective, for a given level of external financing (d and e), entrepreneurs want to minimize the fractions of output paid to lenders ($B(\bar{\omega}, s)$) and to shareholders ($C(\bar{\omega}, s)$) so that firms can receive a higher fraction of the output.

Note that I make a simplifying assumption that debt and equity investors' behavior is passive. Debt and equity investors are not making an optimal portfolio decision between debt and equity. Instead, equity investors commit to invest only in equity but not in debt, and vice versa for debt investors. In this regard, the contract is optimal only from firms' perspective, and the optimal contract might be different in an environment where investors make an optimal portfolio decision between debt and equity.

Solving the financial contract problem, the optimality conditions are given by

$$\frac{A_1}{A_2} = \frac{B_1 + C_1}{B_2 + C_2} \tag{1.1}$$

$$q = \frac{1}{(B + C) - \frac{(B_1 + C_1)}{A_1} A} \tag{1.2}$$

$$i = \frac{1}{1 - q(B + C)} n \tag{1.3}$$

$$e = \frac{qC}{1 - q(B + C)} n \tag{1.4}$$

where A_1, B_1, and C_1 denote partial derivatives of A, B, and C with respect to $\bar{\omega}$, while A_2, B_2 and C_2 denote partial derivatives with respect to s. The interpretation of these optimality conditions is similar to that of Carlstrom and Fuerst (1997). For completeness, I repeat their interpretation. The first important observation is that for any given price of capital q, equations (1.1) and (1.2) pin down $\bar{\omega}$ and s. Also, note that the optimal $\bar{\omega}$ and s depend implicitly on q, but are independent of the level of internal equity. As a result, all entrepreneurs have identical s and $\bar{\omega}$, and thus the expected shares paid to each party $A(\omega, s)$, $B(\omega, s)$, and $C(\omega, s)$ are identical across entrepreneurs. Substituting this result into equations (1.3) and (1.4), the size of the project i and external equity e are defined as functions of q and n. Rewriting the solution of equation (1.3) as $i(q, n)$, and aggregating $\omega i(q, n)$ across entrepreneurs, the law of large numbers implies an aggregate investment good supply function $I^S(q, n) \equiv i(q, n)\left\{1 - \Phi(\bar{\omega})\mu - \left[1 - \Phi\left(\bar{\omega} + \frac{\gamma}{\phi s}\right)\right]\gamma\right\}$, where n is an average (or aggregate) of individual internal equity across entrepreneurs, with a slight abuse of notation. Thus aggregate investment is a function solely of the economy-wide capital price q, and aggregate internal equity n. The linearity of the firms' balance sheet in internal equity is a direct consequence of the assumption that the costs of state verification and profit diversion are linear in the size of project i. Without linearity, the computational burden would increase substantially once the partial equilibrium contract is embedded into a DSGE setting, since it would be necessary to track the distribution of internal equity to solve the model.

The second important observation concerns the expected return on internal saving $\frac{qAi}{n}$. Replacing i with equation (1.3), $\frac{qAi}{n}$ is equal to $\frac{qA}{1-q(B+C)}$. This term is important in understanding the evolution of entrepreneurs' internal equity in a DSGE setting. In the absence of financial frictions, the expected return on internal saving is always equal to one, which implies that returns on debt, external equity and internal equity are identical.[7] Consistent with the Modigliani-Miller theorem, this

[7] q is greater than 1 in equilibrium if financial frictions are present. This essentially reflects a compensation to contractual parties for participating in debt and equity contracts which incur deadweight loss. As a result $q = 1$ in the absence of financial frictions. At the same time $A+B+C =$

further implies that the financing method is irrelevant to entrepreneurs. However, as long as financial frictions are present, there is a deadweight loss from external financing due to the costly state verification and profit diversion. Since lenders, external shareholders, and entrepreneurs internalize the loss, the expected return on internal saving is always greater than one, and from the above expression for $\frac{qAi}{n}$ the size of the expected return depends on the level of debt and external equity.[8] As a result financial structure does matter, and this incentivizes entrepreneurs to adjust internal equity accordingly over time in the DSGE model discussed in Section 1.4.

Lastly, entrepreneurs rely on *both* debt and external equity in equilibrium. In other words, it is not optimal for entrepreneurs to use a single source of external finance. Consider an entrepreneur who finances completely through debt. Intuitively, marginally increasing external equity barely affects the probability of diversion. This implies that external shareholders will not ask for a high premium for buying shares. As a result entrepreneurs will replace debt with equity. Now, consider the opposite case where entrepreneurs finance their project entirely with equity. In this case, marginally increasing debt barely increases the default probability, and this implies a low real borrowing cost. As a result entrepreneurs will replace equity with debt.

1 without financial frictions. Substituting $q = 1$ and $A = 1 - (B + C)$ into $\frac{qA}{1-q(B+C)}$ yields $\frac{qA}{1-q(B+C)} = 1$.

[8]Note that A, B, and C are functions of s and $\bar{\omega}$, and equations (1.1)-(1.4) pin down $\bar{\omega}$, s, i, and e.

1.3.4 Outcome of Financial Contracts

In this section, I present numerical results on the effect of changes in uncertainty on financial contracts in a partial equilibrium setting. In this case, in a partial equilibrium setting, contract parties take the capital price q and internal equity n as fixed. I conduct a comparative statics exercise by changing the value of the dispersion of idiosyncratic productivity σ_ω while holding the capital price q and other parameters fixed, for a given level of internal net worth n. Parameter values used in this exercise are reported under the heading "Financial Friction" in Table 1.1. They are chosen based on a calibration of the DSGE model, which will be discussed in Section 1.4.

Figure 1.1 shows changes in the levels of balance sheet variables for different values of σ_ω. Solid lines represent percentage deviations from the contract outcome under a baseline parameterization (with dispersion of idiosyncratic productivity $\sigma_\omega = 0.2466$) when both debt and equity contract frictions are present. If the level of uncertainty increases (higher values of σ_ω), entrepreneurs raise less external equity as shown in the top-left panel of Figure 1.1. This result is consistent with empirical evidence, reported in Section 1.6, that increased uncertainty is associated with a decrease in equity financing. Furthermore, entrepreneurs scale down the level of debt (top-right panel of Figure 1.1) in response to increased uncertainty. As a consequence, the size of the project shrinks (bottom-left panel of Figure 1.1).

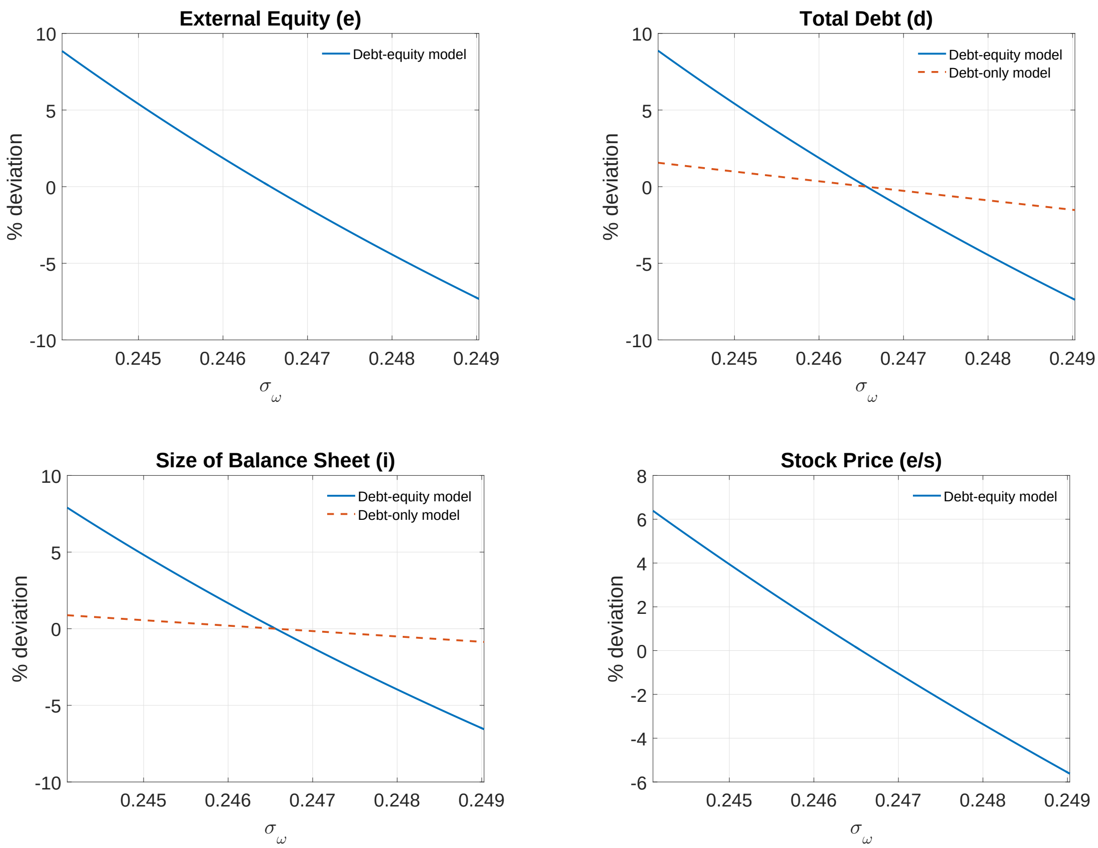
What is the underlying mechanism that drives firms to lower both debt and equity when uncertainty increases? Regarding the debt contract, as uncertainty

Table 1.1: Calibration

Parameter	Description	Debt-only model	Debt-equity model	Target
Preference				
β	Discount factor	0.99	0.99	Standard RBC
ξ	Additional entrepreneurial discount factor	0.9453	0.9084	real borrowing cost $q(1+r_d)-1=60$ bps
ν	Labor disutility	2.8077	2.8049	$h=0.3$
Production				
α	Capital elasticity	0.36	0.36	Standard RBC
κ	Labor elasticity	0.6399	0.6399	Standard RBC
δ	Depreciation rate	0.02	0.02	Standard RBC
Financial Friction				
μ	Costly state verification	0.25	0.25	CF (1997)
γ	Costly profit diversion	-	0.1682	$1-s=0.26$
ϕ	Fraction diverted	-	0.2296	Default rate $\Phi(\bar{\omega})=1.12\%$
$\sigma_{\omega,ss}$	Steady state dispersion of idiosyncratic productivity shocks	0.2466	0.2466	Estimated
Aggregate Shocks				
ρ_θ	Persistence of TFP shocks	0.78	0.78	Estimated
ρ_{σ_ω}	Persistence of uncertainty shocks	0.83	0.83	Estimated
σ_θ	S.D of TFP shocks	0.0071	0.0071	Estimated
σ_{σ_ω}	S.D of uncertainty shocks	0.0469	0.0469	Estimated
$corr\left(\epsilon_{\sigma_\omega,t},\epsilon_{\theta,t}\right)$	Correlation between two shocks	-0.5887	-0.5887	Estimated
Other Parameters				
η	Entrepreneurial mass	0.02	0.02	CF (1997)

Notes: The table shows calibration results of the debt-only model and the debt-equity model. CF (1997) refers to Carlstrom and Fuerst (1997).

Figure 1.1: Partial Equilibrium Analysis - Changes in σ_ω



Notes: The figure shows partial equilibrium contract outcomes for different values of σ_ω. All values are percentage deviations from the contract outcomes calculated at the baseline parameterization ($\sigma_\omega = 0.2466$). Solid lines are contractual outcomes from the debt-equity model. Dashed lines are contractual outcomes from the debt-only model. See Table 1.1 for values of other parameters.

increases, the probability of default increases for any given level of total equity. As a result, lenders find debt securities less attractive, and the lenders' demand for debt decreases. Entrepreneurs find debt financing more expensive since they must compensate lenders for bearing a higher default probability. As a consequence, debt financing decreases in equilibrium.

The model predicts a decrease in equity financing when uncertainty increases, for two reasons. First, for any given level of internal equity n, external equity e, and debt d, the probability of default increases as the level of uncertainty increases, since lower tail risk increases. This implies that it is less likely for entrepreneurs to generate positive profits and dividends. From the external shareholders' perspective, investing in equity becomes less attractive, and as a consequence, shareholders demand equity less. Second, investing in equity is less attractive due to increased upper tail risk. As discussed in the previous section, entrepreneurs are more tempted to divert profits if the realization of the idiosyncratic productivity shock is high. Internalizing the increased chance of profit diversion, shareholders demand equity less. As a result, equity financing decreases in equilibrium. The bottom-right panel of Figure 1.1 shows how external equity per share, or equivalently the price of stock (e/s), varies for different values of σ_ω. It is clear that equity financing becomes more expensive from entrepreneurs' perspective when uncertainty increases, which limits the amount of equity that entrepreneurs can raise.

Answering how firms' capital structure and financing decisions vary in response to uncertainty is itself an important question in corporate finance. However, we are also interested in the macroeconomic consequences of increased uncertainty when equity financing is explicitly taken into account. The most important macroeconomic implication of the model is an *amplification* of uncertainty shocks through the equity financing friction. The amplification of uncertainty arising from equity financing frictions can be shown by comparing contract outcomes in the model with both debt and equity (hereafter the debt-equity model), and the model with only debt (hereafter the debt-only model).

The dashed lines in Figure 1.1 represent percentage deviations from the contract outcome under a baseline parameterization ($\sigma_\omega = 0.2466$) of the debt-only model, which is exactly identical to Carlstrom and Fuerst (1997).[9] As the bottom-left panel of Figure 1.1 shows, the size of the balance sheet responds more to uncertainty in the debt-equity model than in the debt-only model. The amplification arises mainly from the fact that total equity includes both internal equity and external equity in the debt-equity model, but only internal equity in the debt-only model. Since external equity decreases as a result of increased uncertainty, total equity shrinks in the debt-equity model. However, total equity remains constant in the debt-only model. In addition, since total equity determines the debt capacity, shrinking total equity further limits debt financing in the debt-equity model. As the top-right panel of Figure 1.1 suggests, debt financing shrinks more in the debt-equity model when uncertainty increases.

In a general equilibrium setting, internal equity will vary over time in both models, as entrepreneurs adjust internal savings, which form the internal equity of following periods. However, since the debt-equity model has the additional margin of external equity financing, total equity is expected to exhibit larger fluctuations in response to uncertainty shocks in following periods as well.

De Fiore and Uhlig (2011, 2015) investigate the role of bond and bank loan financing over the business cycle. They show that an economy with a well-developed bond market (along with a bank loan market) is less vulnerable to adverse shocks than an economy heavily dependent on the bank loan market (with a less developed bond market), since firms can substitute one from the other in response to shocks. In

[9] An alternative way to shut down equity financing is to set $\gamma \to 0$, so that profit diversion is virtually costless. In this case, entrepreneurs will always divert profits regardless of the size of profit. Since shareholders internalize the fact that profit diversion always occurs, they will never invest in equity. As a result, the equity market collapses.

contrast, my model predicts that having an additional source of external financing amplifies shocks. The different prediction is mainly due to the complementarity between debt and equity. The amount of equity determines the amount of debt a firm can raise in my model. However, there is no such relationship between bank loans and bond financing in De Fiore and Uhlig (2011, 2015), who focus on substitutability between the two types of debt instruments.

1.4 General Equilibrium Analysis

1.4.1 Setup of the Model

In this section, I embed the partial equilibrium financial contract into a dynamic stochastic general equilibrium model. The main goal of this section is to investigate the dynamic effects of uncertainty shocks on financing decisions and macroeconomic outcomes. In contrast to the partial equilibrium analysis, the price of capital goods q and internal equity n are determined endogenously in equilibrium. The model closely follows Carlstrom and Fuerst (1997). The major differences are introducing the equity contract and uncertainty shocks, in the form of a time-varying stochastic dispersion of idiosyncratic productivity.

The economy is populated with a unit mass continuum of economic agents. There are two types of agents in the model: households with fraction $1 - \eta$ and entrepreneurs with fraction η. Households are standard as in conventional real business cycle models. However, entrepreneurs are non-trivial. They have an access to a stochastic technology which transforms consumption goods into capital goods.

The role of entrepreneurs is critical in the model since entrepreneurs are subject to financial frictions when they finance input costs of capital production. Entrepreneurs finance input costs through financial institutions that pool households' funds and invest in debt and equity. Consumption good producing firms are standard. They take labor and capital as inputs and are not subject to financial frictions.

Households are infinitely-lived and risk averse. They maximize expected lifetime utility by optimally choosing consumption c_t^h and leisure l_t where the time endowment is normalized to unity. They discount the future utility with time preference parameter $\beta \in (0, 1)$. Since there is no heterogeneity across households, I study a representative household hereafter. Households accumulate physical capital k_t^h, which earns gross interest $1 + r_t$ and depreciates at the rate δ in the following period. They also earn wage income by supplying labor to consumption good producing firms, at a wage rate w_t. They purchase consumption goods at a price of unity (the consumption good is the numeraire), and they also purchase new capital goods at the end of the period at a price of q_t. The representative household's utility maximization problem at time 0 is formally given as follows:

$$\max_{c_t^h, k_{t+1}, h_t} E_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t^h,\, 1 - h_t\right)$$

subject to

$$c_t^h + q_t k_{t+1} \leqq w_t h_t + r_t k_t + q_t (1 - \delta) k_t.$$

The maximization problem yields the following standard intratemporal and intertemporal optimality conditions:

$$
\begin{aligned}
w_t &= \frac{u_L(t)}{u_c(t)} && (1.5) \\
q_t u_c(t) &= \beta E\left[u_c(t+1)\left\{r_{t+1} + q_{t+1}(1-\delta)\right\}\right]. && (1.6)
\end{aligned}
$$

Identical consumption good producing firms owned by households have access to a constant-returns-to-scale technology given by $Y_t = \theta_t F(K_t, H_t, H_t^e)$. They produce consumption goods Y_t taking the aggregate capital stock K_t, aggregate household labor H_t, and aggregate entrepreneurial labor H_t^e as inputs. The technology is subject to aggregate TFP shocks θ_t, realized at the beginning of period t. Consumption good producing firms are price takers in both input and output markets. Solving their profit maximization problem yields standard capital, household labor, and entrepreneurial labor demand curves given by

$$
\begin{aligned}
r_t &= F_K(t) \\
w_t &= F_H(t) \\
w_t^e &= F_{H^e}(t).
\end{aligned}
$$

In the baseline calibration (see Section 1.4.3 and Table 1.1), entrepreneurial labor plays a minimal role in the consumption good production process. However, it is important to include entrepreneurial labor since it allows entrepreneurs to start a new business with non-zero internal equity in case of default. If entrepreneurial labor is not included, entrepreneurs start a new business with zero internal equity in case of default. Debt and equity contracts are not well defined if entrepreneurs participate in the contract with zero internal equity.

Entrepreneurs indexed by i are infinitely-lived and risk-neutral. They maximize expected lifetime utility by optimally choosing consumption $c^e_{i,t}$ and capital $z_{i,t+1}$. They discount future consumption with a time discount factor $\xi\beta$ where $\xi \in (0, 1)$. Note that entrepreneurs discount the future more than households. This assumption is necessary, since entrepreneurs will otherwise accumulate capital up to the point where self-financing is enough to cover the entire investment project; financial frictions would not play any role in this case. Entrepreneurs form internal equity in two different ways. First, they supply one unit of labor inelastically, and earn wage income. Secondly, they earn returns on the capital stock carried over from the previous period, in the form of consumption goods that can be used as an input for capital production. These two sources define the following equation for entrepreneurs' internal equity:

$$n_{i,t} = w^e_t + z_{i,t}\left(q_t(1-\delta) + r_t\right),$$

which clearly shows that internal equity $n_{i,t}$ is endogenously determined by entrepreneurs' capital accumulation decisions on $z_{i,t}$ in the previous period, in contrast to the partial equilibrium analysis where entrepreneurs take $n_{i,t}$ as given and fixed. Given internal equity, entrepreneurs tap financial institutions to finance the remaining costs of their investment project $i_{i,t}$ with debt and equity. Since the uncertainty shock is realized at the beginning of period t, the realization of the dispersion of idiosyncratic productivity $\sigma_{\omega,t}$ is common knowledge across all parties when financial contracts are made. In the presence of financial frictions in debt and equity contracts, and as long as entrepreneurs rely on external financing to some degree, the return on internal saving (or internal equity) is always greater than the return on external financing. This result, together with entrepreneurs' risk-neutrality, implies that entrepreneurs commit all of their internal equity to the project. Other details of financial contracts are identical to those in the previous section. To avoid complexity, the model abstracts from the possibility of dynamic or repeated contracts. In other words, entrepreneurs make contracts with different lenders and external shareholders each period. Once debt and equity contracts are made, the entrepreneurs' idiosyncratic productivity shocks are realized, and entrepreneurs make debt default and profit diversion decisions. Solvent entrepreneurs divide returns from their project into consumption and physical capital accumulation, which forms the basis of internal equity in the following period. In case of default, entrepreneurs consume zero units of the consumption good, and start a new business in the following period with an initial level of internal equity built by supplying a single unit of labor. Entrepreneurs that divert profits behave as solvent firms.

Formally, the utility maximization problem of solvent entrepreneurs is

$$\max_{c^e_{i,t}, z_{i,t+1}} E_0 \sum_{t=0}^{\infty} (\xi\beta)^t \, c^e_{i,t}$$

subject to

$$
\begin{aligned}
c_{i,t}^{e}+q_{t}z_{i,t+1} &\leqq q_{t}i_{i,t}\tilde{A}_{i,t} && (1.7)\\
i_{i,t} &= \frac{1}{1-q_{t}\left(B_{t}+C_{t}\right)}n_{i,t} && (1.8)\\
n_{i,t} &= w_{t}^{e}+z_{i,t}\left(q_{t}\left(1-\delta\right)+r_{t}\right) && (1.9)
\end{aligned}
$$

where $\tilde{A}_{i,t}$ is the realized fraction of output belonging to an individual entrepreneur. B_t and C_t are the expected share of output paid to lenders and external shareholders, respectively. Solving the maximization problem yields the entrepreneurs' intertemporal Euler equation:

$$
q_{t}=E_{t}\left[\xi\beta\left\{(q_{t+1}(1-\delta)+r_{t+1})\frac{q_{t+1}A_{t+1}}{1-q_{t+1}\left(B_{t+1}+C_{t+1}\right)}\right\}\right]. \qquad (1.10)
$$

As discussed in the previous section, $\frac{q_{t+1}A_{t+1}}{1-q_{t+1}(B_{t+1}+C_{t+1})}$ is the expected return on internal saving. As long as financial frictions are present and entrepreneurs finance externally, this term is greater than one. Comparing equation (1.6) and (1.10), it is clear that entrepreneurs have a stronger incentive to accumulate physical capital (which, in turn, will become next period's internal equity) than households for a given discount rate. If entrepreneurs have the same discount factor as households, they will eventually accumulate enough physical capital that they can finance investment solely with internal equity. To avoid this outcome, I assume that entrepreneurs have an additional discount factor ξ. Another important observation is that the level of internal equity does not affect the above Euler equation, which is a direct consequence of the linearity assumption; entrepreneurs have access to a CRS technology, and the monitoring and diversion costs are linear in the size of the project $i_{i,t}$. The entrepreneur subscript i does not appear in the entrepreneurs' Euler equation (recall that contract terms $\bar{\omega}$ and s are identical across entrepreneurs regardless of the level of internal equity, as shown in section 1.3.3). This allows me to analyze the aggregate economy without tracking the distribution of individual entrepreneurs' internal equity, which reduces the computational burden substantially. Lastly, note that $\tilde{A}_{i,t}$ in equation (1.7) denotes the *realized* fraction of output belonging to an individual entrepreneur. However, it is not necessary to track $\tilde{A}_{i,t}$ of each individual entrepreneur, since aggregation of entrepreneurs' budget constraint across individuals (along with equation (1.8) and (1.9)) yields the following aggregate entrepreneur budget constraint:

$$c_t^e + q_t z_{t+1} = q_t i_t A_t, \tag{1.11}$$

where $\tilde{A}_{i,t}$ in equation (1.7) is replaced by A_t, which by the law of large numbers is the expected share of output paid to the entrepreneur, defined as in Section 1.3.3. Note that there is no entrepreneur subscript i in equation (1.11) due to aggregation. It is possible to further drop subscript i in equations (1.8) and (1.9) after aggregation across entrepreneurs, and to track only aggregate variables.[10] Since the main interest is in the average behavior of agents and aggregate fluctuations, I abstract from subscript i from now on.

[10]To be more precise, one can compute averages by summing across entrepreneurs, then dividing by entrepreneurial mass η.

The role of financial institutions in this model is to channel funds (in consumption goods) from households to entrepreneurs, and to relay capital goods from entrepreneurs to households who want to purchase capital goods (recall that entrepreneurs repay in capital goods to financial institutions). In addition, financial institutions pay households a non-stochastic return from investing in equity and debt, by pooling funds from each household. Since financial institutions invest in the debt and equity of an infinite number of entrepreneurs, they can effectively diversify the risk arising from idiosyncratic productivity shocks. In particular, since there is no aggregate shock realized for the duration of the contract, households receive a gross return of 1 in terms of consumption goods from financial institutions each period regardless of the realized value of uncertainty shocks. However, the time-varying dispersion of idiosyncratic productivity shocks is an *aggregate risk*, and generates business cycles. Uncertainty shocks are aggregate shocks since they affect the terms of debt and equity contracts that *all* entrepreneurs face. As a result uncertainty shocks *do generate* aggregate fluctuations regardless of diversification, as the level of debt and equity financing of all entrepreneurs is affected by changes in the dispersion of idiosyncratic productivity shocks, although households still receive a non-stochastic return.

Market clearing conditions for the two labor markets, the consumption goods market, and the capital goods market are given by

$$
\begin{aligned}
H_t &= (1-\eta)h_t \\
H_t^e &= \eta \\
(1-\eta)c_t + \eta c_t^e + \eta i_t &= \theta_t F(K_t,\, H_t,\, H_t^e) \\
K_{t+1} &= (1-\delta)K_t + \eta i_t \left[1 - \Phi(\bar{\omega})\mu - \left(1 - \Phi\left(\widehat{\omega}\right)\right)\gamma\right]
\end{aligned}
$$

where $K_{t+1} = (1-\eta)k_{t+1} + \eta z_{t+1}$ and $\widehat{\omega} = \bar{\omega} + \frac{\gamma}{\phi s_t}$.

Lastly, I specify laws of motion for aggregate shocks as follows:

$$
log(\sigma_{\omega,t}) = (1-\rho_{\sigma_\omega})log(\sigma_{\omega,ss}) + \rho_{\sigma_\omega} log(\sigma_{\omega,t-1}) + \epsilon_{\sigma_\omega,t} \quad (1.12)
$$

$$
log(\theta_t) = \rho_\theta log(\theta_t) + \epsilon_{\theta,t} \quad (1.13)
$$

where $\epsilon_{\sigma_\omega} \sim \left(0, \sigma^2_{\sigma_\omega}\right)$ and $\epsilon_{\sigma_\omega} \sim (0, \sigma^2_\theta)$.

1.4.2 Definition of Competitive Equilibrium of DSGE Model

A competitive equilibrium is a vector of variables:

$\left\{\bar{\omega}_t,\, s_t,\, i_t,\, e_t,\, c_t^h,\, h_t,\, k_{t+1},\, c_t^e,\, z_{t+1},\, n_t,\, w_t,\, w_t^e,\, r_t,\, q_t,\, H_t^e,\, H_t,\, \theta_t,\, \sigma_{\omega,t}\right\}$ which satisfies

- Household utility maximization:

$$\begin{aligned} w_t &= \frac{u_L(t)}{u_c(t)} \\ q_t u_c(t) &= \beta E\left[u_c(t+1)\left\{r_{t+1} + q_{t+1}(1-\delta)\right\}\right] \end{aligned}$$

- Enterpreneur utility maximization:

$$\begin{aligned} q_t &= E_t\left[\xi\beta\left\{\left(q_{t+1}(1-\delta) + r_{t+1}\right)\frac{q_{t+1}A_{t+1}}{1 - q_{t+1}\left(B_{t+1} + C_{t+1}\right)}\right\}\right] \\ c_t^e + q_t z_{t+1} &= q_t A_t i_t \\ n_t &= w_t^e + z_t\left(q_t\left(1-\delta\right) + r_t\right) \end{aligned}$$

- Optimal financial contract:

$$\begin{aligned} \frac{A_{1,t}}{A_{2,t}} &= \frac{B_{1,t} + C_{1,t}}{B_{2,t} + C_{2,t}} \\ q_t &= \frac{1}{(B_t + C_t) - \frac{(B_{1,t} + C_{1,t})}{A_{1,t}} A_t} \\ i_t &= \frac{1}{1 - q_t\left(B_t + C_t\right)} n_t \\ e_t &= \frac{q_t C_t}{1 - q_t\left(B_t + C_t\right)} n_t \end{aligned}$$

- Factor price:

$$
\begin{aligned}
r_t &= F_K(K_t,\, H_t,\, H_t^e) \\
w_t &= F_H(K_t,\, H_t,\, H_t^e) \\
w_t^e &= F_{H^e}(K_t,\, H_t,\, H_t^e)
\end{aligned}
$$

- Market clearing conditions:

$$
\begin{aligned}
H_t &= (1-\eta)h_t \\
H_t^e &= \eta \\
(1-\eta)c_t + \eta c_t^e + \eta i_t &= \theta_t F(K_t,\, H_t,\, H_t^e) \\
K_{t+1} &= (1-\delta)K_t + \eta i_t \left[1 - \Phi(\bar{\omega})\mu - (1-\Phi\left(\tilde{\omega}\right))\,\gamma\right]
\end{aligned}
$$

- Laws of motion of aggregate shocks:

$$
\begin{aligned}
log(\sigma_{\omega,t}) &= (1-\rho_{\sigma_\omega})log(\sigma_{\omega,ss}) + \rho_{\sigma_\omega} log(\sigma_{\omega,t-1}) + \epsilon_{\sigma_\omega,t} \\
log(\theta_t) &= \rho_\theta log(\theta_t) + \epsilon_{\theta,t}
\end{aligned}
$$

where $K_{t+1} = (1-\eta)k_{t+1} + \eta z_{t+1}$, and $\{\epsilon_{\sigma_\omega,t}\, \epsilon_{\theta,t}\}$ are a vector of exogenous shocks, and $\{A_t,\, B_t,\, C_t,\, A_{1t},\, B_{1t},\, C_{1t},\, A_{2t},\, B_{2t},\, C_{2t}\}$ is defined identically as in section 1.3.3.

1.4.3 Calibration

I calibrate the model at a quarterly frequency. The calibration strategy is designed to ensure comparability between the debt-equity model and the debt-only model. To achieve this goal, I closely follow the calibration strategy of Carlstrom and Fuerst (1997) and Chugh (2016). The former is used as a benchmark debt-only model, and the latter investigates the transmission of uncertainty shocks under an almost-identical setting as in Carlstrom and Fuerst (1997). Table 1.1 summarizes calibrated parameter values.

For both the debt-equity model and debt-only model, the household discount factor is set to $\beta = 0.99$, which is standard. Household preference is $u(c, 1-h) = ln(c) + \nu(1-h)$, where I calibrate ν so that households' labor supply h_{ss} is equal to 0.3 in the steady state.

For both models, the production function $F(K_t, H_t, H_t^e) = K_t^{\alpha} H_t^{\kappa} H_t^{e\,(1-\alpha-\kappa)}$. I set $\alpha = 0.36$, $\kappa = 0.6399$ and the capital depreciation rate $\delta = 0.02$, following standard RBC models.

A careful calibration of parameters characterizing debt and equity contracts is absolutely crucial to making a reasonable comparison between the debt-only and debt-equity models, since the role of financial frictions embedded in debt and equity contracts in the transmission of uncertainty shocks is our main interest. For the monitoring cost in case of default, I set $\mu = 0.25$ in both models. Although the cost of bankruptcy is directly observable to some degree, different studies report different values for μ. For example Altman (1984) documents that the costs of default, such as legal costs and lost sales and profits, are approximately 20 percent of total assets, while Alderson and Betker (1995) report costs of approximately 36 percent of total assets. However, the focus of this research is not on precisely estimating the cost of bankruptcy, but instead, on *comparing* two models. For the reason, I simply use the value assumed in Carlstrom and Fuerst (1997).

The calibration of remaining parameters $\sigma_{\omega,ss}$, ξ, γ, and ϕ is more complicated. For both models, the long-run average uncertainty is set to $\sigma_{\omega,ss} = 0.2466$, which I estimate from firm-level data as described in Section 1.6.1. I calibrate ξ of the debt-only model targeting a 240 basis points annualized real cost of borrowing in steady state ($q(1+r_d)-1 = 60bps$). The target moment is the average of the Baa-Treasury spread for the sample period 1993-2014.[11] Under this parameterization, the debt-only model implies steady state quarterly default rate $\Phi(\bar{\omega}_{ss}) = 1.12\%$, which is slightly higher than the rate from Dun & Bradstreet data (quarterly default rate of 0.97%) cited by Carlstrom and Fuerst (1997). I use this value to calibrate the equity financing friction parameters of the debt-equity model.

For the debt-equity model, there are three remaining financial contract parameters, ξ, γ, and ϕ. I calibrate the parameters jointly targeting a 1.12% quarterly default rate (which is implied by the debt-only model), a 240 basis point annualized real borrowing cost on the debt contract, and an entrepreneurial share $(1-s)$ of 0.26 in the steady state. The target moment for the steady state entrepreneurial share mostly follows Holderness et al. (1999). They document that the average managerial

[11] The data can be downloaded from the Federal Reserve Economic Data. In particular, the name of the series is "Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity" and the corresponding series ID is "BAA10Y".

stock ownership of top 40th to 50th percentile firms by size is 16.2% in 1935 and 24.4% in 1995. I select a 26% share for 2005, the midpoint of the sample period 1993-2014, by linear extrapolation of the long-term trend implied by Holderness et al. (1999).[12]

For both models, I am able to exactly match all targeted moments. Under the parameterization reported in Table 1.1, the two models have exactly identical real costs of borrowing and default rates on debt in the steady state, implying that I can investigate the role of equity financing frictions in the transmission of uncertainty shocks by comparing the two models.

Parameter values characterizing the laws of motion of aggregate shocks (at a quarterly frequency) are calibrated to match annual persistence parameters and the variance-covariance matrix for TFP and uncertainty, as estimated from data. I calculate aggregate TFP using annual data on labor and capital inputs. Using aggregate TFP and the benchmark measure of uncertainty constructed in Section 1.6.1, I estimate persistence parameters and the variance-covariance matrix of uncertainty and TFP shocks at an annual frequency.[13] Then, I calibrate quarterly persistence parameters, and the variance-covariance matrix, using a simulated method of moments. In particular, I generate simulated series of uncertainty and TFP shocks for 400,000 quarters, convert simulated series into annual frequency, estimate annual persistence parameters and the variance-covariance matrix using simulated series

[12]Leverage is not a targeted moment. The steady state leverage ratio is 0.565 and 0.560 for the debt-only model and the debt-equity model respectively. The corresponding data moment for leverage, defined as total assets over total liabilities, is 0.468. When defined as total debt over total assets, the data moment is 0.203.

[13]The data availability allows me to measure uncertainty only at an annual frequency. See Section 1.6.1 for details.

converted to an annual frequency, and match annual persistence parameters and the variance covariance matrix from data. This procedure yields a quarterly persistence parameter of uncertainty shocks (ρ_{σ_ω}) of 0.83. This estimate is similar to Chugh (2016) who reports a persistence parameter of 0.83, estimated using data from the Longitudinal Research Database. My persistence is lower than Christiano et al. (2014) who estimate a persistence of 0.95. I estimate a standard deviation of uncertainty shocks $\sigma_{\sigma_\omega} = 0.0469$. This result is in line with previous empirical findings which document that σ_{σ_ω} ranges from 0.0374 to 0.07 (Christiano et al., 2014, Chugh, 2016). The quarterly persistence parameter of TFP shocks (ρ_θ) is 0.78. This estimate is slightly lower than the value reported in the large-scale DSGE model estimation literature (Christiano et al., 2014). The standard deviation of TPF shocks is $\sigma_\theta = 0.0071$, similar to standard RBC literature (King and Rebelo, 1999). The correlation between uncertainty and TFP shocks ($corr\left(\epsilon_{\sigma_\omega,t}, \epsilon_{\theta,t}\right)$) is -0.5887. This is consistent with the notion that uncertainty increases during recessions, as I document further in Section 1.6.1.

1.5 Numerical Results

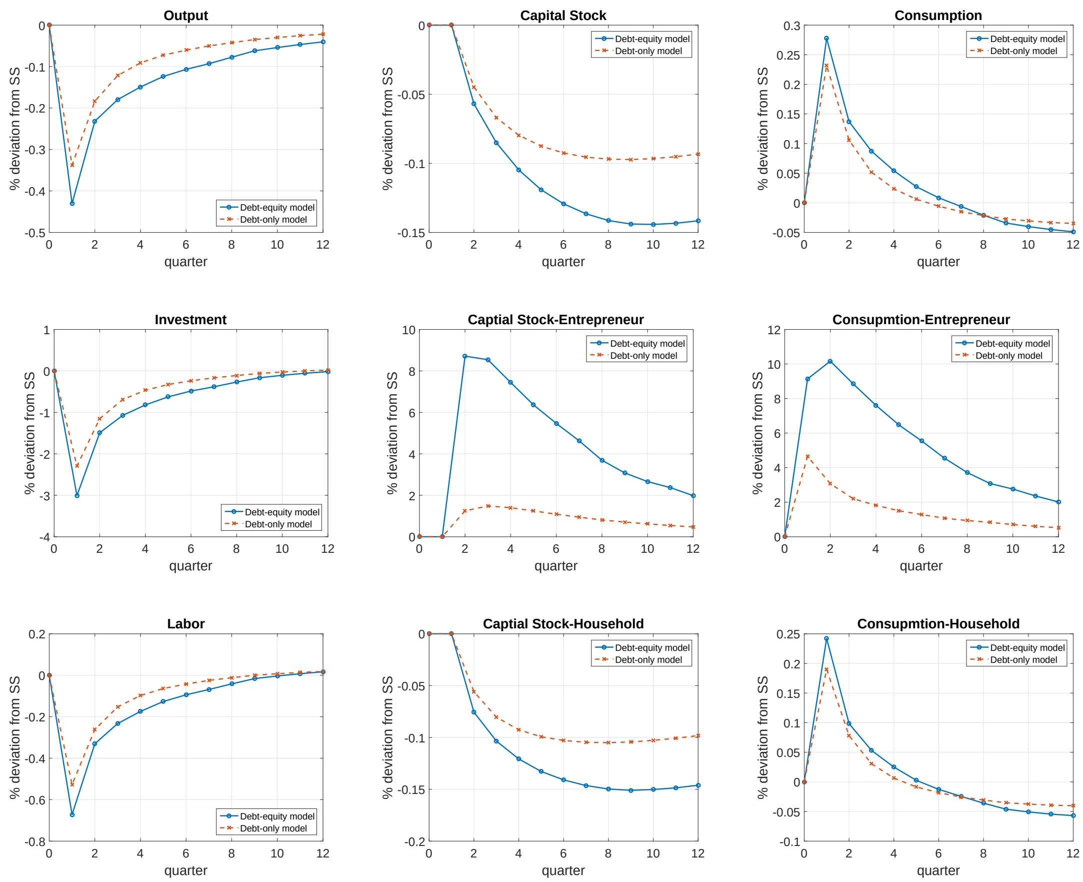
1.5.1 Impulse Response Analysis

There are two goals of the impulse response analysis. The first is to understand how uncertainty shocks affect firms' financing decisions, especially equity financing decisions. The second is to understand how the response of macroeconomic variables to uncertainty shocks is *amplified* through equity financing frictions. In particular, I compare impulse response functions to uncertainty shocks of the debt-equity model with those from the debt-only model to highlight the amplification mechanism that is unique to the debt-equity model.

1.5.1.1 Dynamic Effect of Uncertainty Shocks

I numerically solve the model defined in Section 1.4.2 with a 3rd-order approximation around the deterministic steady state. The impulse I consider in this section is a one-time one-standard-deviation increase in the dispersion of idiosyncratic productivity, holding the level of aggregate TFP at its steady state. In other words, I do not take the correlation between the two shocks into account in calculating impulse response functions. Under the current calibration, this equals roughly a 4.7% increase in σ_ω, from 0.246 to 0.257. Figures 1.2 to 1.4 present impulse response functions of main variables of interest to the uncertainty shock for the debt-equity model (solid lines with circles), and the debt-only model (dashed lines with 'x'). Starting with balance sheet variables, on impact, entrepreneurs in the debt-equity model immediately downsize debt financing to approximately 4% below the steady state level (top-right panel of Figure 1.3). As uncertainty increases, downside risk increases, which results in an increased default probability (3rd-row left-column of Figure 1.4). As a result, debt financing becomes more expensive, and the real borrowing cost increases (2nd-row left-column of Figure 1.4) which induces entrepreneurs to lower debt financing compared to the steady state. This transmission channel of uncertainty shocks through debt financing frictions has already been discussed widely in the previous literature (Christiano et al., 2014, Gilchrist et al., 2014, Chugh, 2016), and the debt-equity model is consistent with previous findings.

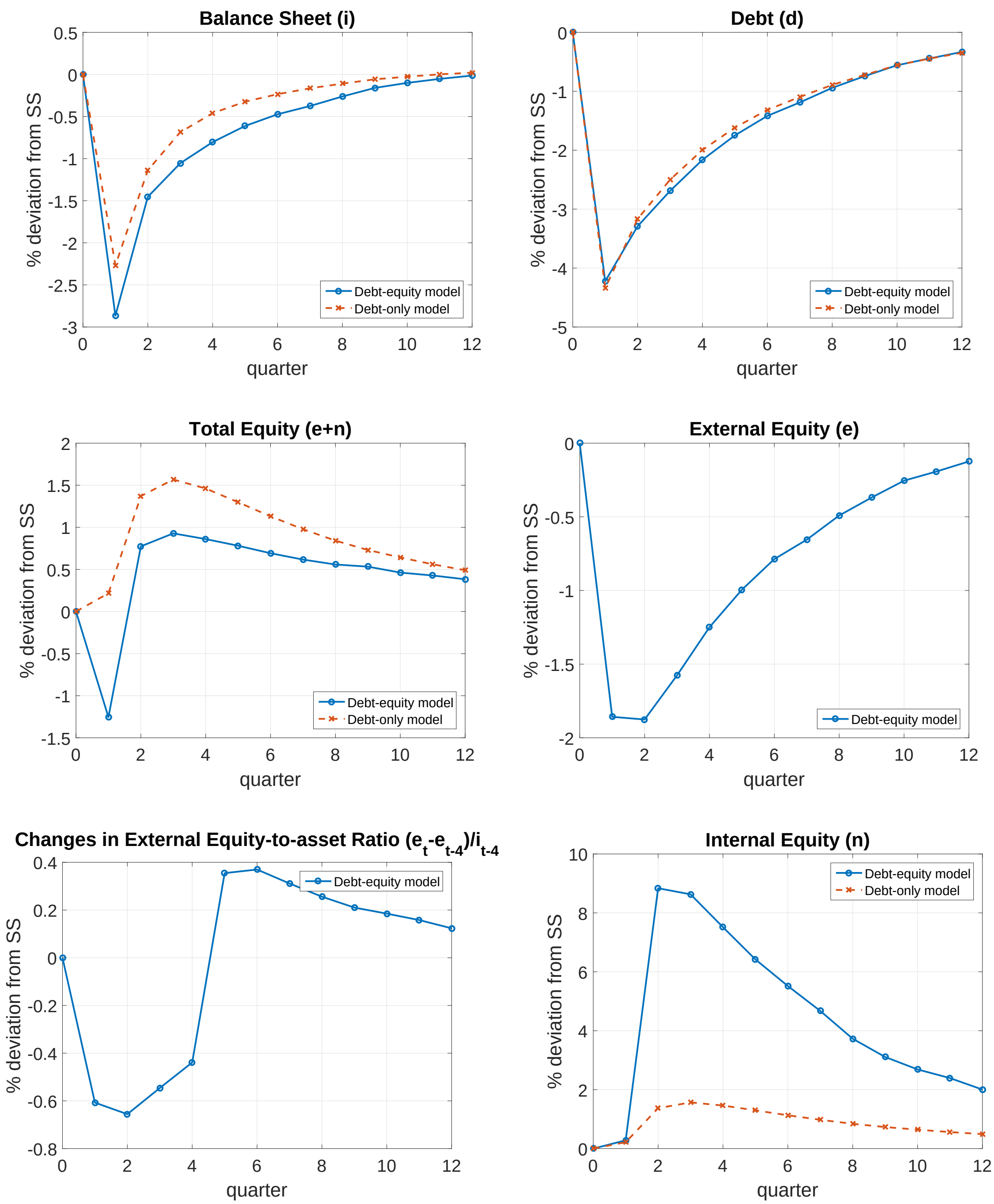
Figure 1.2: IRF in response to Uncertainty Shock - Aggregate variables



Notes: The figure shows impulse response functions of aggregate variables to a one-time one-standard-deviation increase in uncertainty shocks. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

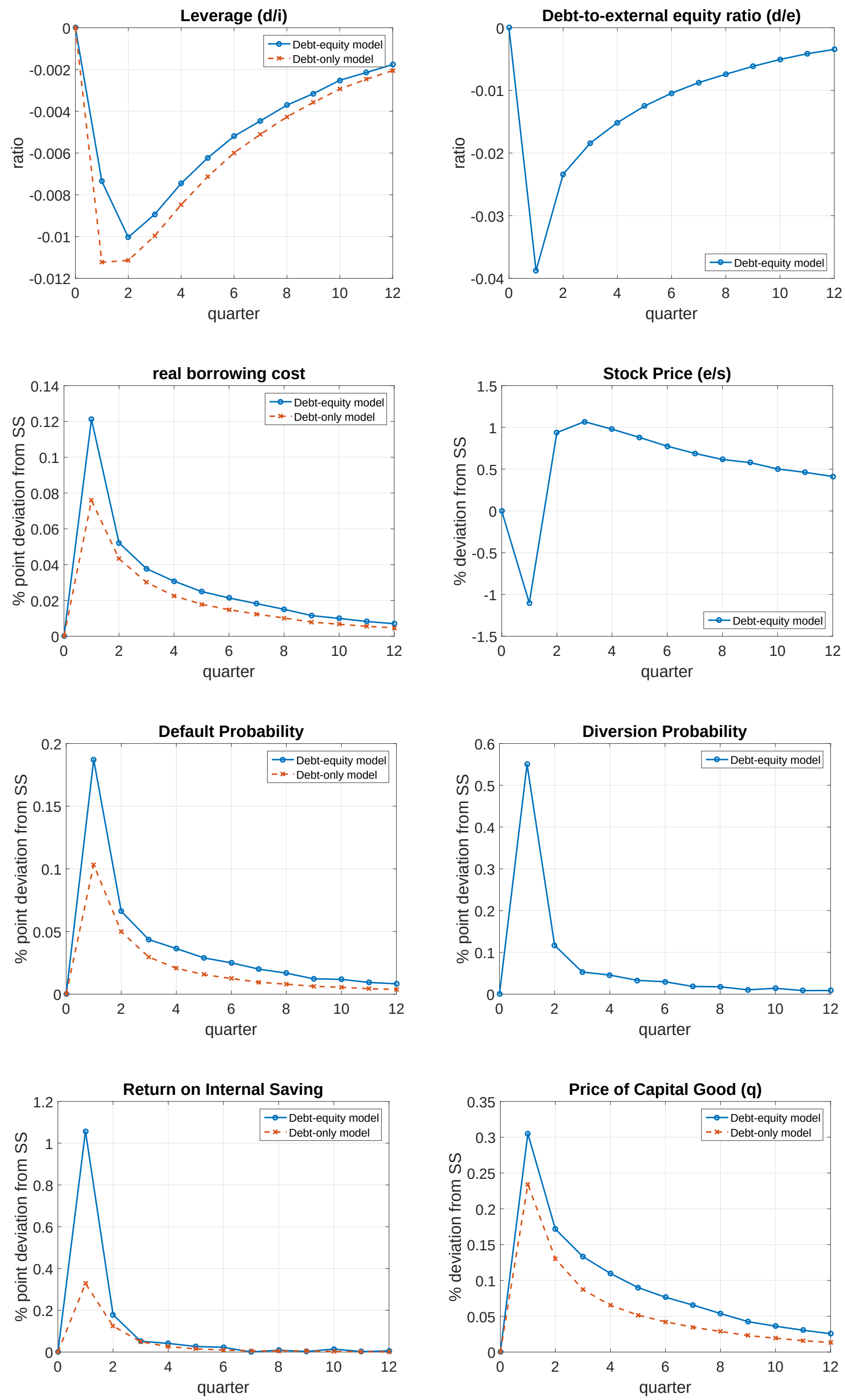
However, the debt-equity model also has unique implications coming from equity financing frictions. As uncertainty increases, entrepreneurs raise less external equity than in the steady state. As discussed in the partial equilibrium analysis, increased uncertainty makes investing in external equity less attractive for two reasons. First, an increased downside risk implies that capital good producing firms

Figure 1.3: IRF in response to Uncertainty Shock - Balance Sheet



Notes: The figure shows impulse response functions of balance sheet variables to a one-time one-standard-deviation increase in uncertainty shocks. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

Figure 1.4: IRF in response to Uncertainty Shock - Others financial variables



Notes: The figure shows impulse response functions of other financial variables to a one-time one-standard-deviation increase in uncertainty shocks. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

are more likely to default, and thus less likely to generate positive profit. Secondly, increased upside risk increases entrepreneurs' temptation to divert profit (3rd-row right-column of Figure 1.4). As a result, equity financing becomes more costly to entrepreneurs, as the amount of equity they raise by selling a unit of shares s, or equivalently the stock price e/s, decreases (2nd-row right-column of Figure 1.4), which discourages entrepreneurs from raising external equity (middle-right of Figure 1.3).

The last remaining item of the liability side of the corporate balance sheet is internal equity. Internal equity becomes more valuable as external financing becomes more costly. Clearly, increased uncertainty makes both debt and equity financing more costly. As a result, entrepreneurs are strongly motivated to accumulate internal capital (bottom-right of Figure 1.3 and 4th-row left-column of Figure 1.4). Note that entrepreneurs in the debt-equity model have a stronger incentive to build internal equity than those in the debt-only model. While there is a single source of agency costs in the debt-only model, the debt-equity model has an additional source of agency costs, namely equity financing frictions. As a result, internal saving provides a higher return in the debt-equity model than in the debt-only model in response to adverse uncertainty shocks (4th-row left column of Figure 1.4).

Total equity shrinks immediately and sharply on impact in the debt-only model as external equity shrinks, and overshoots above the steady state in following periods as entrepreneurs start to build internal equity to overcome the higher cost of external financing (middle-left of Figure 1.3). Overall, the size of the balance sheet shrinks persistently, since downward pressure from debt and external equity is greater than the upward pressure from internal equity (Top-left of Figure 1.3).

Comparing the impulse responses of balance sheet variables from the two models, it is clear that the effect of uncertainty shocks is amplified in the debt-equity model. I decompose the amplification effect arising from the equity contract into two components: the *direct* and *indirect* effect. As discussed above, decreasing external equity financing directly affects the size of the balance sheet. Total equity falls on impact and does not increase as much in subsequent periods compared to the debt-only model, since a persistent decrease in external equity offsets the increase in internal equity.

The indirect effect comes from the fact that the level of total equity determines the debt capacity. As total equity decreases on impact, entrepreneurs' debt capacity shrinks. As a result, debt financing is further limited when external equity decreases. In subsequent periods, total equity does not increase as much compared to the debt-only model. This creates an additional downward pressure on debt financing compared to the debt-only model. However, the impulse response functions of debt suggest that the indirect effect is small quantitatively.

Next, I discuss fluctuations of aggregate variables. Since capital good producing firms are subject to financial frictions, uncertainty shocks affect the aggregate economy mostly through the investment channel. Since the size of the balance sheet shrinks, investment falls immediately on impact (middle-left panel of Figure 1.2). Since the supply of capital goods decreases, the stock of capital and aggregate output decreases in response to uncertainty shocks. Again, the effect of uncertainty shocks is amplified in the debt-equity model since the balance sheet of capital producers shrinks more in the debt-equity model.

One potentially counter-factual prediction of the model is the impulse response function of consumption (3rd column of Figure 1.2). Aggregate consumption is counter-cyclical in response to uncertainty shocks. As discussed in Barro and King (1984) and Chugh (2016), standard RBC models do not predict a procyclical impulse response function of consumption to shocks that do not affect the marginal productivity of labor or labor supply directly. The uncertainty shock falls into that category.

Since the model is solved with a 3rd-order approximation, I can examine whether there are non-linear effects of uncertainty shocks. First, I compare impulse response functions to a one-time one-standard-deviation increase and decrease in uncertainty (hereafter a 1-SD adverse and favorable shock, respectively) generated by the debt-equity model. Figure 1.5 reports impulse response functions of key variables to these two shocks. The peaks of the main financial variables (cost of borrowing, default probability, and diversion probability) generated by a 1-SD adverse shock are slightly larger than the troughs generated by a 1-SD favorable shock. The outcomes of financial contracts affect firms' investment decision directly, and as a consequence the trough of investment in response to a 1-SD adverse shocks is slightly larger than the peak. However, regardless of these slight differences, the shapes of the impulse response functions to these two shocks are largely symmetric implying, that asymmetries in the effects of uncertainty shocks are only of second order importance.

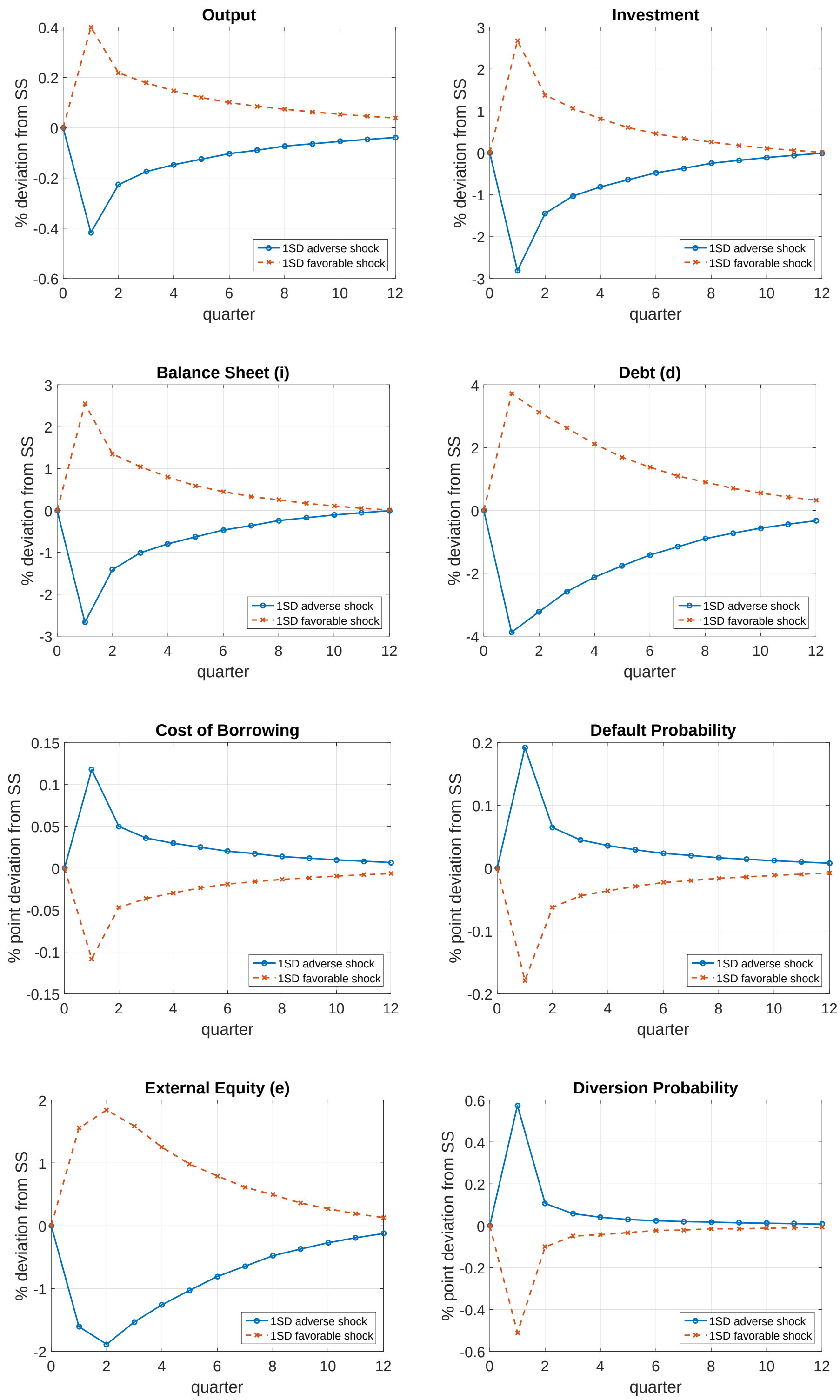
I also compare impulse response functions to one-standard-deviation and two-standard-deviation adverse uncertainty shocks generated by the debt-equity model. Results reported in Figure 1.6 non-linearities are virtually nonexistent; the impulse response functions to a two standard deviation shock are almost identical to the impulse response functions to a one standard deviation shocks scaled by a factor of two.

Financial frictions in debt and equity contracts are the core channel of the transmission mechanism in my model. The two contractual parties, firms and financial institutions, are assumed to be risk neutral. As a result, the effects of uncertainty shocks are captured mostly by linear terms, while non-linear effects of uncertainty shocks remain limited. However, I do not conclude that non-linear effects would not matter in a richer model. The present model is simplified to highlight the role of equity financing in amplification of uncertainty shocks. Studying non-linear effects requires a richer model which is beyond the scope of this research.

1.5.1.2 Dynamic Effect of TFP Shocks

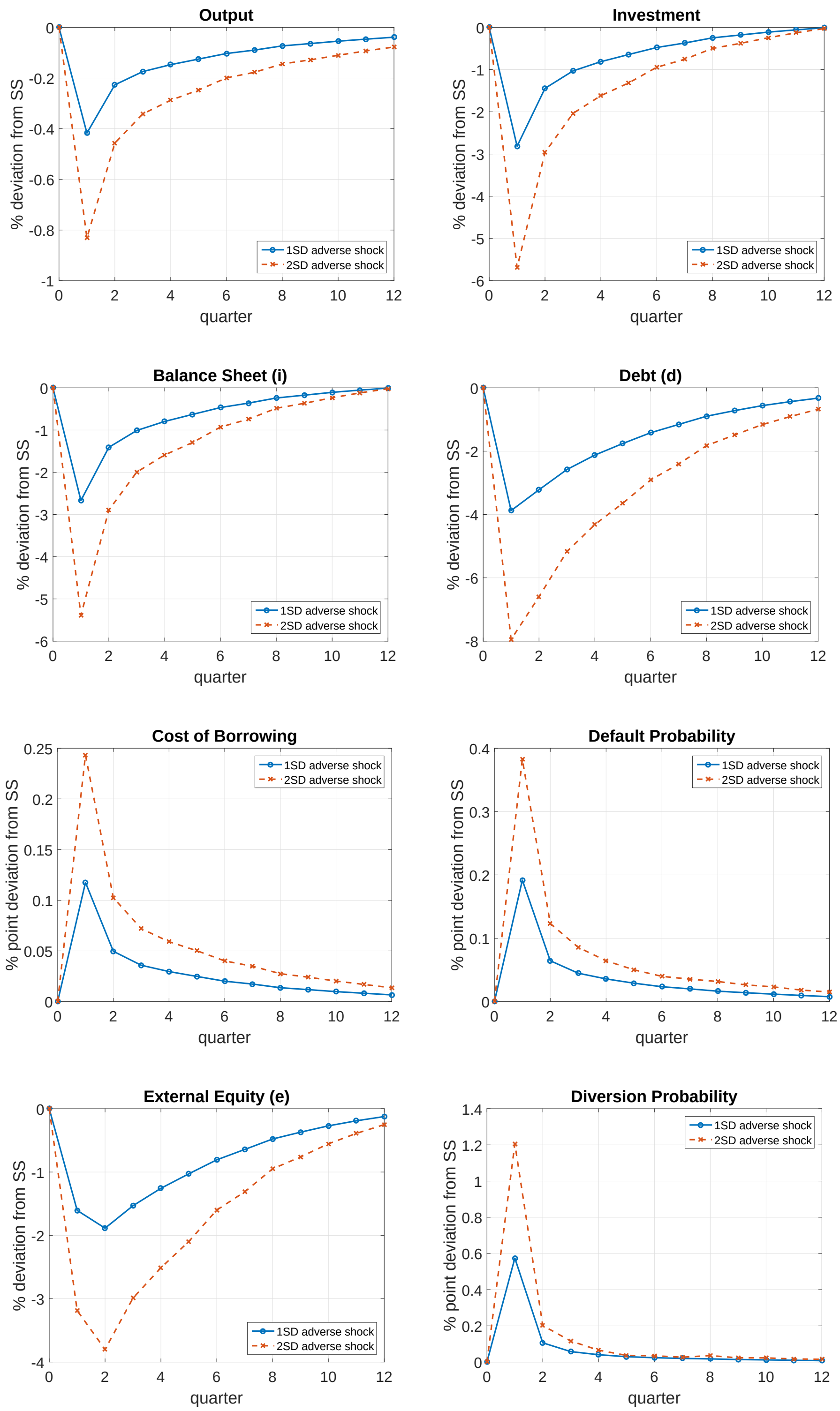
In this section, I investigate how the model responds to a one-time one standard deviation decrease in TFP, holding uncertainty fixed at its steady state level. This is approximately an 0.7% drop in TFP from the steady state. Impulse responses to the TFP shock are shown in Figures 1.7 to 1.9. As reported in Figure 1.8, both debt and external equity financing decrease in response to negative TFP shocks (top-right and middle-right panel of Figure 1.8). However, the underlying reason for decreasing external financing is different from the case of uncertainty

Figure 1.5: IRF in Response to Adverse and Favorable Uncertainty Shock



Notes: The figure shows impulse response functions to one-time one-standard-deviation increases and decreases in uncertainty generated by the debt-equity model. Solid lines are IRFs to adverse uncertainty shocks and dotted lines are IRFs to favorable uncertainty shocks.

Figure 1.6: IRF in Response to 1-SD and 2-SD Uncertainty Shock



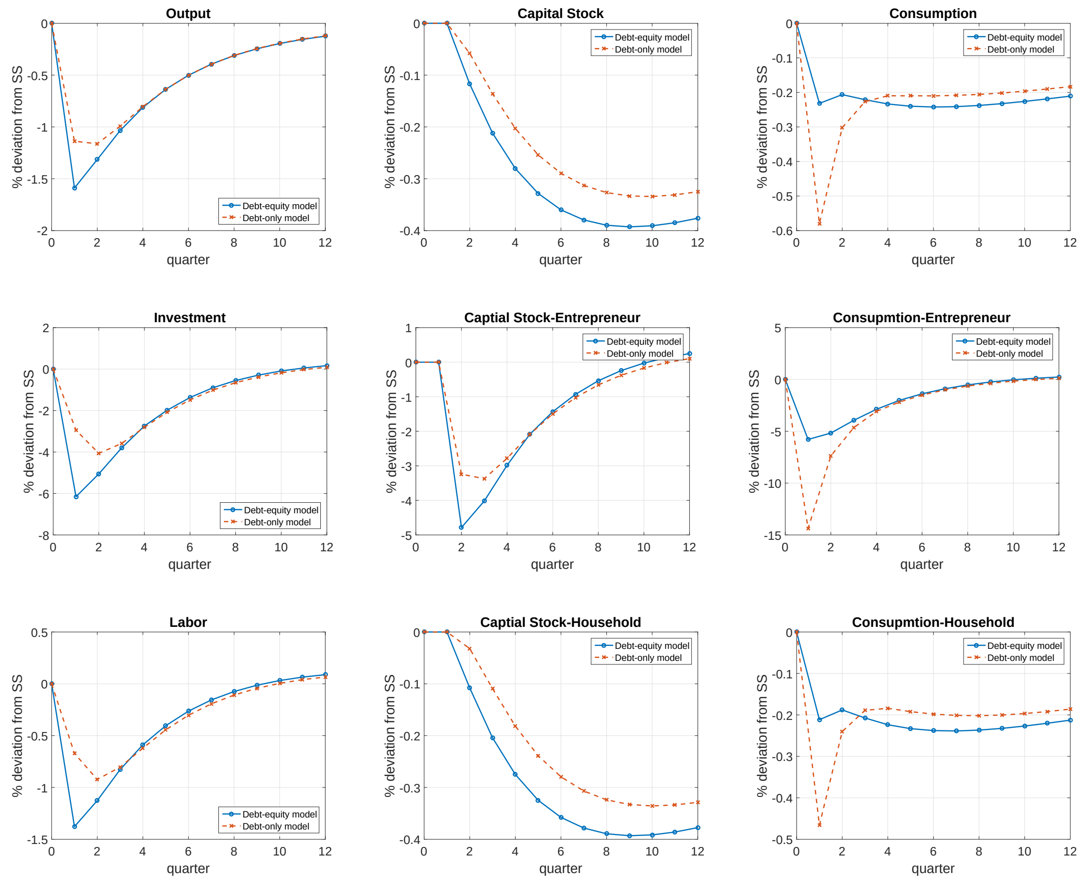
Notes: The figure shows impulse response functions to one-time one-standard-deviation and two-standard-deviation increases in uncertainty generated by the debt-equity model. Solid lines are IRFs to 1-SD uncertainty shocks and dotted lines are IRFs to 2-SD uncertainty shocks.

shocks. Since the marginal product of capital decreases in response to decreased TFP, households demand less capital goods. As a result, entrepreneurs reduce the size of the balance sheet not because of tighter financial constraints, but simply to meet a reduced demand for capital goods. This is also reflected in a decrease in the price of capital (4th-row right-column of Figure 1.9). Entrepreneurs reduce debt and external equity financing for any given level of internal equity. In other words, the demand for credit shifts in. As a result, both the default probability and the diversion probability decrease (3rd-row left-column and 3rd-row right-column of Figure 1.9), which leads to a decreasing real borrowing cost (2nd-row left-column in Figure 1.9). Internal equity shrinks too (bottom-right and middle-right panel of Figure 1.8), since agency costs decrease, which implies a decrease in the return on internal saving (4th-row left-column of Figure 1.9).

The debt-equity model predicts a larger amplification of macroeconomic variables in response to TFP shocks compared to the debt-only model. However, the amplification is concentrated at the early stage of the dynamics. In response to negative productivity shocks, entrepreneurs downsize their balance sheet in response to the reduced demand for capital goods. In the debt-equity model, entrepreneurs have two margins of *active* adjustment, debt and external equity, while in the debt-only model, entrepreneurs only have a single margin of adjustment. Recall from equations (1.3) and (1.4) that the levels of debt and external equity financing are linear functions of the level of internal equity. Thus, the size of the balance sheet shrinks at a faster rate in the debt-equity model per unit decrease in internal equity.

Aggregate variables are all positively correlated with TFP shocks as expected.

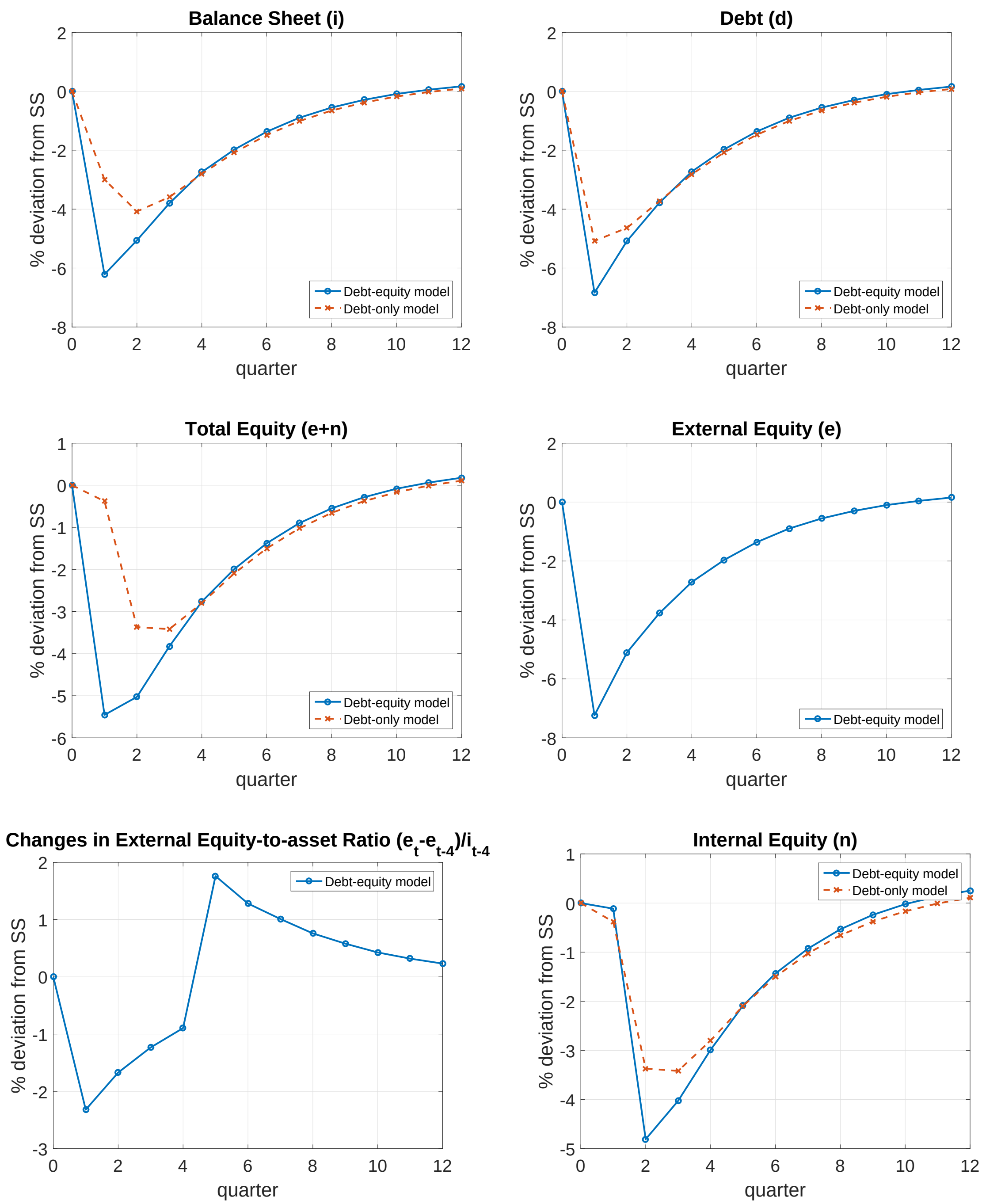
Figure 1.7: IRF in response to Productivity Shock - Aggregate variables



Notes: The figure shows impulse response functions of aggregate variables to a one-time one-standard-deviation decrease in TFP. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

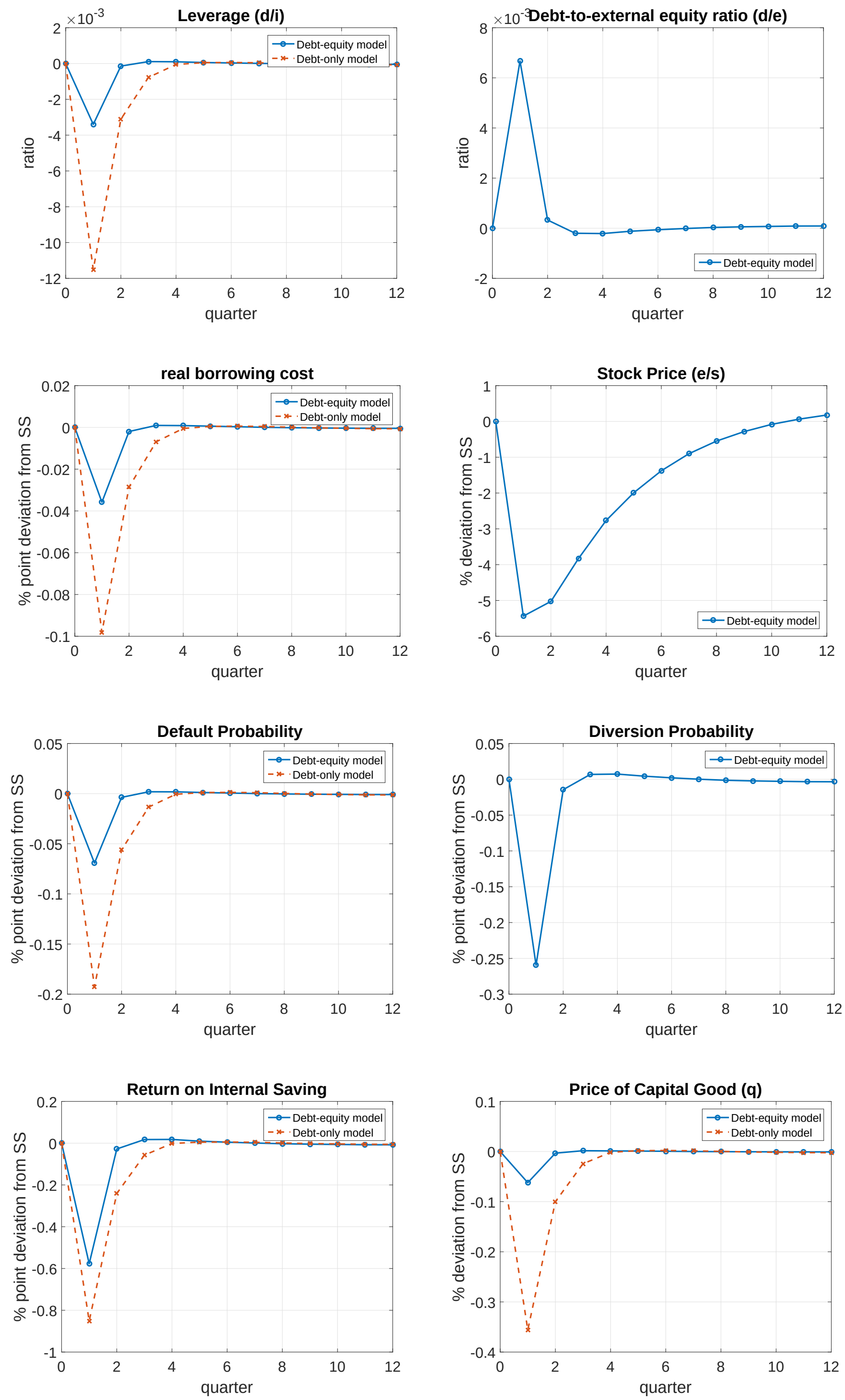
Output falls mostly because of the decrease in TFP and the capital stock. The decrease in investment and the capital stock is a direct consequence of the decrease in the size of the balance sheet. Impulse response functions of aggregate variables to TFP shocks are amplified in the debt-equity model relative to the debt-only model. This is a direct consequence of the different dynamics of the size of the balance sheet. In contrast to the case of uncertainty shocks, consumption decreases as well.

Figure 1.8: IRF in response to Productivity Shock - Balance Sheet



Notes: The figure shows impulse response functions of balance sheet variables to a one-time one-standard-deviation decrease in TFP. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

Figure 1.9: IRF in response to Productivity Shock - Other financial variables



Notes: The figure shows impulse response functions of other financial variables to a one-time one-standard-deviation decrease in TFP shocks. Solid lines are from the debt-equity model. Dashed lines are from the debt-only model.

1.5.2 Simulation: Countercyclical External Financing Costs

In this section, I simulate the model economy to investigate its cyclical properties. I account for the estimated variance-covariance matrix of TPF and uncertainty shocks as described in Section 1.4.3. Note that the correlation between two shocks is -0.5587 which is consistent with the notion that uncertainty increases during recessions. I simulate the model economy for 3,000 quarters where the initial 100 periods are dropped, which is a standard procedure.

Table 1.2 reports the correlation coefficients of macroeconomic variables with aggregate output. The first column shows the sample correlation from the data for the sample period 1993Q1-2014Q4. Output, consumption, investment and stock price are logged. All data moments are calculated using HP-filtered series with a smoothing parameter $\lambda = 1,600$. Both consumption and investment are highly procyclical. I use the Baa-Treasury spread and the delinquency rate of industrial and commercial loans to calculate the data moments for real borrowing cost and the default rate, respectively. Both real borrowing cost and the default rate are countercyclical, which suggests that debt financing frictions worsen during recessions. I use the Russell 3000 index as my measure of the stock price, which is highly procyclical, implying that entrepreneurs can raise more equity by issuing shares during booms. In other words, equity financing is less costly during upturns.

The second and the third column of Table 1.2 report the model moments. The most important finding is that, consistent with the data, the debt-equity model generates a countercyclical real borrowing cost and default rate while the debt-only

Table 1.2: Simulation - Cyclicality of Macroeconomic Variables

Variable	Data	Debt-only model	Debt-equity model
Output	1.00	1.00	1.00
Consumption	0.84	0.68	0.41
Investment	0.87	0.96	0.96
Real borrowing cost, $q(1+r_d)-1$	-0.50	0.11	-0.57
Default rate, $\Phi(\bar{\omega})$	-0.76	0.37	-0.50
Stock price, e/s	0.82	-	0.87
Diversion probability, $1-\Phi(\widehat{\omega})$	-	-	-0.31

Notes: The table reports the correlation between each macroeconomic variable and aggregate output. I simulate the economy for 3000 quarters where initial the 100 periods are dropped. Output, consumption, investment, and stock price are logged before sample statistics are calculated. I use the Baa-Treasury spread (FRED series ID: BAA10Y) to calculate the data moment for the real borrowing cost. I use the delinquency rate of industrial and commercial loans (FRED series ID: DRBLACBS) to calculate the data moment for the default rate. I use the Russell 3000 index (FRED series ID: RU3000PR) to calculate the data moment for the stock price. All data moments are calculated using HP-filtered series with a smoothing parameter $\lambda = 1600$. The sample period is 1993Q1-2014Q4.

model generates the opposite. The additional amplification of uncertainty shocks due to equity financing frictions is key to explaining the difference between the two models. In both models, the real borrowing cost and the default rate decrease in response to negative TFP shocks, as discussed above. In contrast, adverse uncertainty shocks increase both the default risk and the cost of borrowing. If the effect of adverse uncertainty shocks dominates the effect of adverse TFP shocks, then the model will generate a countercyclical real borrowing cost and default rate. It turns out that the effect of uncertainty shocks dominates in the debt-equity model, but not in the debt-only model. In the debt-equity model, entrepreneurs cannot delever as much as they do in the debt-only model since equity financing is also limited due to increased uncertainty (see leverage in Figure 1.4). This is the fundamental reason why the increase in the default rate and the real cost of borrowing is fur-

Table 1.3: Simulation - Cyclicality of Balance Sheet Variables

Variable	Debt-only model	Debt-equity model
Balance sheet, i	0.96	0.96
Debt, d	0.95	0.95
External equity, e	-	0.96
Total equity, $e+n$	0.59	0.88
Leverage, d/i	0.79	0.72

Notes: The table reports correlations between each balance sheet variables and aggregate output. I simulate the economy for 3000 quarters, where the initial 100 periods are dropped, a standard procedure. All variables are logged except leverage.

ther amplified in the debt-equity model. At the same time, the debt-equity model also predicts countercyclical equity financing costs. This is shown by the countercyclical diversion probability and the procyclical stock price. Adverse uncertainty shocks play a key role, as increased uncertainty worsens agency costs arising from the equity contract.

Table 1.3 reports the cyclicality of balance sheet variables. Since adverse TPF and uncertainty shocks both affect both debt and equity financing negatively, financing variables are all procyclical. These findings are consistent with previous empirical studies, for example Covas and Den Haan (2011).

In sum, the simulation result shows that the debt-equity model predicts both procyclical debt and equity financing, and countercyclical default and external financing costs. In contrast, the debt-only model fails to generate a countercyclical default rate and real cost of borrowing, which reconfirms the importance of equity financing frictions that amplify the effect of uncertainty shocks. This finding is important, as existing literature is unable to explain the coexistence of procyclical debt and equity financing and countercyclical external financing costs (Covas and Den Haan, 2012, Jermann and Quadrini, 2006, 2012).

Both the debt-only and the debt-equity model generate procyclical investment and consumption (Table 1.2). For both models, investment is highly procyclical and the cyclicality is slightly stronger than the data. In contrast, consumption is substantially less procyclical in both models compared to the data. This is mainly due to the response of consumption to adverse uncertainty shocks. Consumption increases in response to adverse uncertainty shocks on impact (top-right of Figure 1.2), while it decreases in response to adverse TFP shocks (top-right of Figure 1.7). Considering that the correlation coefficient of uncertainty and TFP shocks is negative $corr\left(\epsilon_{\sigma_\omega,t}, \epsilon_{\theta,t}\right) = -0.5887$, the decrease in consumption due to negative TFP shocks is offset on average by the increase in consumption due to adverse uncertainty shocks in many cases. As a result, the procyclicality of consumption is weaker in both models. Since uncertainty shocks are more amplified in the debt-equity model than in the debt-only model, the procyclicality of consumption is weaker in the debt-equity model.

1.6 Empirical Evidence

Uncertainty shocks have real consequences by affecting firms' decisions over debt and equity financing. While previous studies mostly focus on the role of debt financing as a potential transmission channel of uncertainty shocks (Gilchrist et al., 2014, Christiano et al., 2014), this paper highlights the importance of equity financing. Thus, it is important to show empirically how firms' equity financing decisions respond to changes in uncertainty.

In this section, I document the relationship between firms' equity financing decisions and the level of uncertainty and provide suggestive evidence that uncertainty and equity financing are negatively correlated. To do so, I construct a measure of uncertainty taking a bottom-up approach. I estimate firm-level revenue-based total factor productivity (TFPR) using annual balance sheet data of U.S. listed firms from Compustat, and define uncertainty as the cross-sectional standard deviation of estimated firm-level TFPR.[14] This approach directly matches the model counterpart of uncertainty, which is the dispersion of firms' idiosyncratic productivity shocks. I then document how firms' equity financing decisions are associated with the level of uncertainty by closely following the regression-based approach of Covas and Den Haan (2011), who document cyclical patterns of debt and equity financing. I close the section with various robustness tests, which all suggest a negative relationship between the level of uncertainty and equity financing.

1.6.1 Measuring Uncertainty

I follow Wooldridge's extension of Levinsohn and Petrin (2003) to estimate firm-level revenue-based total factor productivity. I first estimate the following production function using firm-level data for a particular industry:

$$\ln\left(VA_{i,j,t}\right) = \beta_j + \beta_j^L \ln L_{i,j,t} + \beta_j^K \ln K_{i,j,t} + \epsilon_{i,j,t} \tag{1.14}$$

[14] I use total factor productivity (TFP) and revenue-based total factor productivity (TFPR) interchangeably hereafter within Section 1.6. They both refer to TFPR.

where $VA_{i,j,t}$, $L_{i,j,t}$ and $K_{i,j,t}$ represent value-added, the number of employees, and the beginning-of-period capital stock of firm i, in industry j, at time t respectively.[15] I use annual balance sheet data of U.S. listed firms from Compustat for the sample period 1990 to 2014. Utility and financial firms are excluded from the sample. Equity financing has become an important source of external financing since the early 1980s, so it would be preferable to estimate firm-level TFPR for a sample period including the early 1980s. However, the sample period starts in 1990 due to limited data availability of the industry-level value-added deflator, the intermediate goods price deflator, and the average annual wage, which are necessary for the estimation. I use a 2-digit North American Industry Classification System (NAICS) level value-added price deflator from the Bureau of Economic Analysis to convert nominal $VA_{i,j,t}$ into real terms. 3- and 4-digit deflators are used when available. Beginning-of-period capital stocks are deflated using the aggregate non-residential fixed investment deflator. Although the Bureau of Labor Statistics provides an investment good price deflator at the 2- and 3-digit NAICS level, the series starts only in 1990. Since the stock of capital is built by summing the sequence of investment over time, it is necessary to know the price deflator of investment goods purchased prior to 1990, unless the firm's investments are all made after 1990. For this reason, there is a substantial loss of observations if an industry level investment good price deflator is used instead of the aggregate price deflator.

Although it is more common to use plant-level data to estimate factor elasticities and productivity (Olley and Pakes, 1996, Levinsohn and Petrin, 2003), I use

[15] See Appendix A.1 for details of how variables are constructed.

firm-level data, since plant-level data is usually available only for the manufacturing sector, which imposes a substantial limit on the scope of analysis. By using firm-level data, it is possible to extend the scope of analysis beyond manufacturing.

Since it is common to assume that each industry has different factor elasticities of labor and capital, I allow β_j^L and β_j^K to vary across industry j, and estimate the production function separately for each industry at the 2-digit NAICS level. The estimation results for 18 industries are reported in Table 1.4. The estimation results seem reasonable, as the sum of labor and capital elasticities is 0.87 on average across industries.

We can further decompose total factor productivity $\epsilon_{i,j,t}$ into $e_{i,j,t}$, which is known to firms based on past information (or in other words, is a rational forecast of productivity) and $u_{i,j,t}$, which is a pure *shock* component ($\epsilon_{i,j,t} = e_{i,j,t} + u_{i,j,t}$). The model defines uncertainty as the dispersion of idiosyncratic productivity *shocks*. Hence, it is necessary to estimate $u_{i,j,t}$ using estimated $\hat{\epsilon}_{i,j,t}$. To do so, I assume that the firm-level productivity evolves following an AR(1) process:

$$\hat{\epsilon}_{i,j,t} = \rho\hat{\epsilon}_{i,j,t-1} + \eta_i + \lambda_{j,t} + u_{i,j,t}. \tag{1.15}$$

Following Bloom et al. (2012) and Gopinath et al. (2015), the equation (1.15) includes an industry-time-fixed effect $\lambda_{j,t}$ in order to capture a time-varying industry-wide component of total factor productivity. In this research, it is particularly important to distinguish aggregate (or industry-level) and idiosyncratic components of TFP considering that the main focus of this research is to investigate the effect of

Table 1.4: Factor Elasticities

Industry (2-digit NAICS)	Num. of obs	Labor (β_j^L)	Capital (β_j^K)	$\beta_j^L + \beta_j^K$
Agriculture, Forestry, Fishing and Hunting (11)	294	0.45	0.33	0.78
Mining, Quarrying, and Oil and Gas Extraction (21)	4,583	0.34	0.49	0.83
Construction (23)	1,117	0.78	0.10	0.89
Manufacturing (31)	4,096	0.48	0.32	0.80
Manufacturing (32)	10,472	0.64	0.15	0.79
Manufacturing (33)	25,139	0.64	0.11	0.74
Wholesale Trade (42)	3,467	0.77	0.17	0.94
Retail Trade (44)	3,539	0.75	0.19	0.94
Retail Trade (45)	2,011	0.60	0.19	0.79
Transportation and Warehousing (48)	2,712	0.35	0.50	0.85
Information (51)	11,049	0.81	0.06	0.87
Professional, Scientific, and Technical Services (54)	4,326	0.93	0.11	1.04
Administrative and Support and Waste Management and Remediation Services (56)	2,110	0.75	0.17	0.91
Educational Services (61)	334	0.89	0.12	1.01
Health Care and Social Assistance (62)	1,340	0.77	0.23	0.99
Arts, Entertainment, and Recreation (71)	622	0.39	0.25	0.64
Accommodation and Food Services (72)	2,389	0.62	0.24	0.87
Other Services (except Public Administration) (81)	345	0.80	0.21	1.01

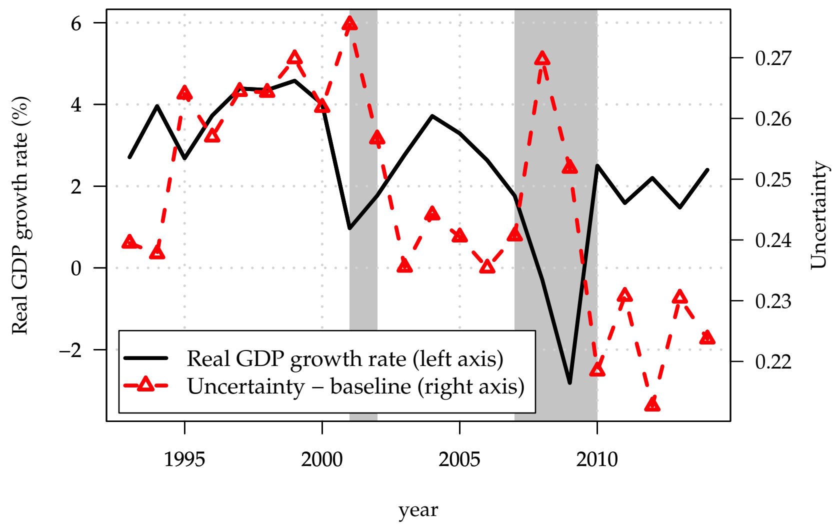
Notes: The table reports the results (factor elasticities) from estimating a production function separately for each industry at a 2-digit NAICS level. The estimation methodology follows Wooldridge's (2009) extension of Levinsohn and Petrin (2003). Wooldridge 2009 changes in the within-industry dispersion of *idiosyncratic* productivity. I define the OLS residual $\hat{u}_{i,j,t}$ from estimating equation (1.15) as the idiosyncratic productivity shock of firm i in industry j at time t.

The TFP estimation yields a total of 68,379 firm-year TFP observations for 8,416 unique firms, which is approximately 85% of the sample used in the main regression discussed in the next section, both in terms of the number of observations and unique firms. There are fewer observations available for the variables required to construct TFP than for the main regression.[16] I do not require firms included in the main regression to have all the information required to be included in the TFP regression. I follow this strategy to maximize the number of observations for the main regression.

The construction of my measure of uncertainty follows naturally as the weighted average of the industry-level standard deviation of idiosyncratic productivity *shocks* at a given year t: $Uncertainty_t = \sum_j w_j \times SD_{j,t}(\widehat{u}_{i,j,t})$ where $SD_{j,t}(\widehat{u}_{i,j,t})$ is the within-industry cross-sectional standard deviation of $\widehat{u}_{i,j,t}$ at a given period t and w_j is a time-invariant weight for each industry given by the fraction of aggregate value-added accounted for by industry j. Time-invariant weights ensure that uncertainty does not vary over time due to changes in industry composition. Figure 1.10 shows the annual GDP growth rate and $Uncertainty_t$ for the sample period 1993-2014. $Uncertainty_t$ spikes up during the recessions in 2001 and 2008, consistent with the notion that uncertainty increases during recessions.

[16] Note for instance that there is an additional loss of observations from estimating equation (1.15) since an observation at t is dropped if an observation at $t-1$ is missing.

Figure 1.10: Uncertainty and Real GDP Growth



Notes: The figure shows aggregate uncertainty, $Uncertainty_t$ (solid line) and annual real GDP growth (dotted line with triangles) for the sample period 1993-2014. $Uncertainty_t$ is defined as the standard deviation of firm-level TFP shocks. See equation (1.14) and (1.15) along with the main text for the details of calculation. Annual real GDP growth is defined as the log difference of real GDP (multiplied by 100). Shaded areas show NBER recession dates. 2001-2014.
Source: Author's calculation, Compustat, Bereau of Economic Analysis

1.6.2 Uncertainty and Cyclicality of Equity Financing

Following Covas and Den Haan (2011), I take a regression approach to investigate the relationship between uncertainty and equity financing, using annual balance sheet data of U.S. listed firms from Compustat for the sample period 1993 to 2014.[17] Utility and financial firms are excluded from the sample. If a firm-year observation violates the accounting identity that total assets equals total liabilites

[17]Note that I estimate firm level TFP for a sample period starting in 1990, not 1993. This is solely because of observations lost due to lagged variables. In estimating TFP, lagged values of dependent variables are required. As a result, observations in 1990 are lost. In estimating equation (1.15), an additional year of observations are lost. This allows me to construct $Uncertainty_t$ starting only in 1992. Lastly, I include lagged $Uncertainty$ as an additional regressor (see equation (1.16)) which results in an additional loss of observations in 1992.

plus stockholders' equity by more than 10%, it is dropped from the sample in order to ensure data reliability. I describe the definition and construction of variables in more detail in Appendix A.1. Table 1.5 reports sample statistics of firm characteristics for the entire sample. There are 78,149 firm-year observations from 10,595 unique firms. On average, approximately 3,500 observations (or firms) are available per year. The number of firms in the sample is similar to related previous studies using Compustat, for example Fama and French (2005).

On average, sample firms have assets worth \$3,200 million 2009 USD. The distribution of total assets is skewed to the right. Firms' average sales are approximately \$2,600 million 2009 USD, and this distribution is also skewed to the right. Net stock sales are on average 14% of beginning-of-period total assets (or lagged total assets). This number is similar to Fama and French (2005), who document that average equity issues by listed firms in the U.S. in a given year during 1993-2002 represent 12.6% of total assets.

The bottom half of Table 1.5 reports summary statistics of firm-year observations for the subset of data with positive net stock sales. There are 43,994 firm-year observations associated with positive net stock sales, accounting for approximately 55% of the entire sample of firm-year observations. There are 9,481 unique firms, roughly 95% of all unique firms in the entire sample, that experience positive net stock sales at least once during the sample period. On average, firms report four years of positive net stock sales (43,994 firm-year observations with positive net stock sales divided by 10595 unique firms). Considering that, on average, sample firms have seven years of observations (78,149 firm-year observations divided by

Table 1.5: Sample Statistics

Firm_type	Num of Obs	Num of firms	Variable	Mean	SD	Min	Median	Max
All	78149	10595	Total assets	$ 3,202.49	$ 11,519.22	$ 1.19	$ 230.68	$109,919.10
			Sales	$ 2,631.94	$ 9,061.47	$ 0.06	$ 213.79	$ 83,021.44
			Net stock sales	14.20%	51.25%	-300.00%	0.08%	300.00%
			Gross stock sales	15.80%	51.00%	0.00%	0.43%	300.00%
			Tobin's Q	3.42	8.05	0.28	1.61	85.96
			Debt-to-asset Ratio	0.20	0.19	0.00	0.17	0.77
Net Issuer	43994	9481	Total asset	$ 1,980.09	$ 8,343.25	$ 1.19	$ 171.42	$109,919.10
			Sales	$ 1,553.83	$ 6,185.23	$ 0.06	$ 146.55	$ 83,021.44
			Net stock sales	27.26%	65.18%	0.00%	1.31%	300.00%
			Gross stock sales	27.68%	65.52%	0.00%	1.48%	300.00%
			Tobin's Q	4.57	9.95	0.28	1.94	85.96
			Debt-to-asset Ratio	0.19	0.19	0.00	0.14	0.77

Notes: The table reports summary statistics of the sample. The top half of the table reports summary statistics for the entire sample, while the bottom half reports statistics for firm-years with positive net stock sales. Total assets (AT) and sales (SALE) are measured in terms of millions of 2009 constant U.S. Dollars. Net stock sales are measured as sales of common and preferred stock (SSTK) minus purchases of common and preferred stock (PRSTKC) normalized by beginning-of-year total assets, which equal lagged total assets (AT). Gross stock sales are measured as sales of common and preferred stock (SSTK) normalized by beginning-of-year total assets. Capital letters in parentheses represent Compustat variable mnemonics. Tobin's Q is measured as the book-to-market value ratio of total assets. The debt-to-asset ratio is measured as total debt divided by total assets. See Appendix A.2 for details of variable definitions. Gross and net stock sales are winsorized at 300% and -300%. All other variables are winsorized at the top and bottom 0.5 percentiles.
Source: Compustat

10,595 unique firms), approximately half of the observations per firm are associated with positive net stock sales.

Table 1.5 reveals important differences between net equity issuers compared to other firms. Net equity issuers are smaller in terms of asset size and total sales, and have higher growth opportunities as measured by Tobin's Q. This is consistent with predictions of corporate finance theories, that smaller firms with high growth opportunities actively issue equity in financial markets.

The specification of the main regression equation is

$$Equity\,finance_{i,t} = \eta_i + \sum_{p=0}^{L=1} \theta_p \Delta RGDP_{t-p} + \sum_{p=0}^{L=1} \beta_p Uncertainty_{t-p} + \gamma X_{i,t} + \epsilon_{i,t} \quad (1.16)$$

where $Equity\,finance_{i,t}$ is the net amount of external equity raised by firm i at time t, $\Delta RGDP_t$ is the real GDP growth rate, $Uncertainty_t$ is the level of uncertainty, and $X_{i,t}$ is a vector of firm-level control variables. A firm fixed effect η_i is included to control for time-invariant firm-specific factors that could affect financing decisions. I measure $Equity\,finance_{i,t}$ as net sales of stock normalized by lagged total assets as in Covas and Den Haan (2011). While $Equity\,finance_{i,t}$ can be measured in other ways, for example as changes in stockholders' equity at book or market value, net sales of stock is strictly preferred considering that this paper highlights the role of equity raised by selling stock to outside shareholders. Note that the book value of equity changes not only due to sales of stock but also due to changes in retained earnings. Considering that retained earnings are defined as profits that are not paid to stockholders, they should be considered as an internal source of financing.

Meanwhile, the market value of stockholders' equity may vary for reasons other than sales of stock or changes in retained earnings. For example, if stock prices change, the market value of equity changes regardless of firms' financing decisions or changes in retained earnings. However, net sales of stock cannot be changed by retained earnings or changes in stock price, unless firms decide to engage in a financial contract with external shareholders and sell shares.

Table 1.6 summarizes the size and the frequency of equity issuance in the sample. Approximately 75% of the observations are associated with positive gross stock sales, which suggests that equity issuance is common among listed firms in the U.S. In terms of size, approximately 40% of the observations are associated with gross stock sales greater than 1% of lagged total assets. It is also notable that a non-negligible fraction of observations are associated with sizable equity issuance relative to the existing size of the firm (greater than 3% of total assets). Net stock sales show a similar pattern. Approximately 50% of observations report positive net stock sales and approximately 20% of the observations are associated with net equity issuance that exceeds 3% of lagged total assets. Figure 1.11 shows the distribution of net and gross stock sales.

The vector $X_{i,t}$ of firm-level control variables includes cash flow, Tobin's Q, sales growth, asset growth,[18] and firm size as measured by the log of beginning-of-period total assets (or lagged total assets). These variables are chosen mostly following Korajczyk and Levy (2003), Fama and French (2005), Covas and Den Haan

[18]Cash flow, sales growth, and asset growth are all normalized by lagged total assets. See Appendix A.2 for a precise definition of variables.

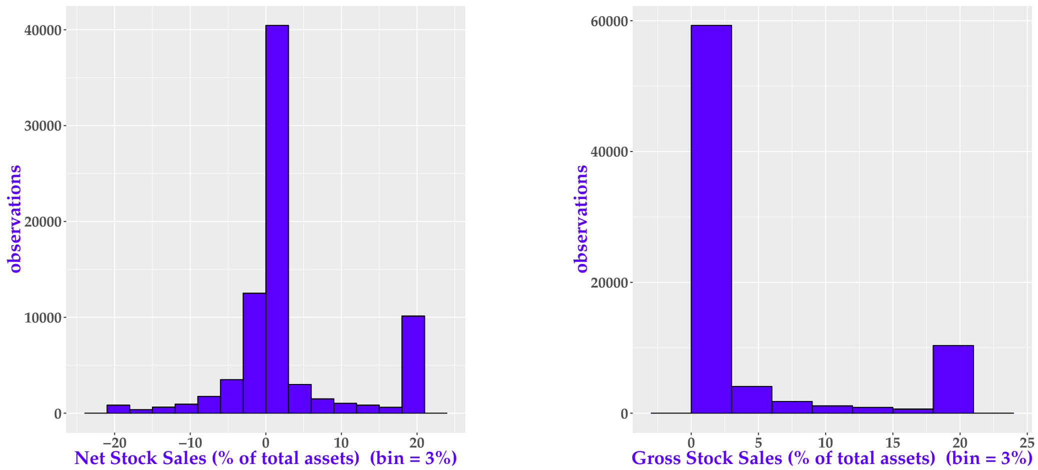
Table 1.6: Frequency of Equity Financing

Interval	Gross Stock Sales		Net Stock Sales	
	Frequency	Percentage	Frequency	Percentage
less than 0%	-	-	20,563	26.31%
0%	18,659	23.88%	13,592	17.39%
0∼1%	30,060	38.46%	20,180	25.82%
1∼3%	10,563	13.52%	6,681	8.55%
greater than 3%	18,867	24.14%	17,133	21.92%
Total observations	78,149	100%	78,149	100%

Notes: The table shows the number of observations and relative frequency of positive gross and net stock sales. Gross and net stock sales are defined as in Table 1.5; Net stock sales are measured as sales of common and preferred stock (SSTK) minus purchases of common and preferred stock (PRSTKC) normalized by beginning-of-year total assets, or lagged total assets (AT). Gross stock sales are measured as sales of common and preferred stock (SSTK) normalized by beginning-of-year total assets.
Source: Compustat

(2011), and Erel et al. (2012), all of which report firm-level variables that are closely related to firms' financing decisions. Higher cash flows imply that firms have more internal funds to finance production and investment projects. The pecking order theory predicts that firms prefer internal sources of funds to external financing, since external financing is more expensive due to information asymmetry problems that affect financial contracts. Hence, firms with higher cash flow are expected to have lower net stock sales. Tobin's Q measures firms' growth opportunities. If firms have higher growth opportunities, they are more likely to raise external funds, in addition to using internal funds. This implies that firms with higher Tobin's Q are likely to have higher net stock sales. Sales growth is potentially related to external financing in two opposite ways. Holding firms' profitability constant, higher sales growth possibly implies that more internal funds are available, in which case

Figure 1.11: Distribution of Net and Gross Stock Sales



Notes: The left panel shows the distribution of net stock sales. The right panel shows the distribution of gross stock sales. Gross and net stock sales are defined as in Table 1.5; Net stock sales are measured as sales of common and preferred stock (SSTK) minus purchases of common and preferred stock (PRSTKC) normalized by beginning-of-year total assets, or lagged total assets (AT). Gross stock sales are measured as sales of common and preferred stock (SSTK) normalized by beginning-of-year total assets. Capital letters in parentheses represent Compustat variable mnemonics. The size of bin is 3%. For both panels, the largest bin includes all observations greater than 20%. The smallest bin includes all observations less than -20%. See Table 1.6 for more details of the distribution.
Source: Compustat

firms are less likely to issue equity to finance production and investment projects. However, it is also possible that firms experience higher sales growth when they are expanding their business rapidly. In this case, firms may need to issue more stock to meet financing needs that cannot be covered solely with internal funds. Finally, higher asset growth is likely to be associated with positive net stock sales, since faster growing firms are less likely to be able to meet their financing needs solely with internal funds.

Firm size is included since firms in different size classes exhibit different financing patterns over the business cycle. Covas and Den Haan (2011) document that smaller firms tend to exhibit stronger procyclicality for both debt and equity financing compared to larger firms, while in contrast the largest firms (top 1% of Compustat firms) raise equity countercyclically.

$Equity\, finance_{i,t}$ is winsorized at 300% and -300%.[19] All other firm-level variables are winsorized at the top and bottom 0.5 percentiles.

Table 1.7 summarizes the estimation results of equation (1.16). I use a least square dummy variable (LSDV) estimator to estimate the panel regression model. To show that the sample is consistent with the previous empirical literature on the cyclicality of equity financing, I first estimate the regression model without $Uncertainty$. Spec 1 shows that equity financing is positively correlated with real GDP growth both contemporaneously and in lags, consistent with previous empirical literature.

Spec 2 - 3 show that the level of uncertainty is negatively correlated with firms' equity financing decisions in lags. Spec 4, which controls for the largest set of firm characteristics, suggests that the level of uncertainty is negatively correlated with equity financing, both contemporaneously and in lags. Results are statistically significant at 1% for all specifications. The economic significance of uncertainty is also non-negligible. A one standard deviation marginal increase in uncertainty, which is 0.018, results in a roughly 0.7 percentage point decrease in net sales of stock both simultaneously and in lags.[20] In other words, an average firm with total

[19] The top and bottom 0.5 percentiles of $Equity\, finance_{i,t}$ are 957% and -25% respectively. Since the distribution of $Equity\, finance_{i,t}$ is substantially skewed, winsorizing at the top and bottom 0.5 percentiles seems insufficient. However, the baseline results do not change in case of winsorizing at the top and bottom 0.5 percentiles.

[20] Note that net sales of equity are normalized by lagged total assets. So, the exact interpretation of the point estimate is that there is a 0.7 percentage point decrease in the "net equity sales-to-total assets ratio." in response to a 1 standard deviation increase in uncertainty.

Table 1.7: Aggregate uncertainty and net stock sales

	(1) Spec 1	(2) Spec2	(3) Spec 3	(4) Spec 4
$RGDP\, growth_t$	0.0077***	0.0078***	0.0061***	-0.00020
	(9.91)	(8.38)	(6.50)	(-0.21)
$RGDP\, growth_{t-1}$	0.0024***	0.0021*	0.0016	0.0013
	(3.18)	(1.80)	(1.44)	(1.17)
$Cashflow_{i,t}$	-0.20***	-0.20***	-0.12***	-0.12***
	(-14.80)	(-14.84)	(-8.57)	(-8.47)
$Tobin's\, Q_{i,t}$	0.035***	0.035***	0.015***	0.013***
	(42.07)	(42.09)	(15.71)	(13.61)
$Sales\, growth_{i,t}$			-0.015*	-0.031***
			(-1.93)	(-4.20)
$Total\, asset\, growth_{i,t}$			0.16***	0.15***
			(25.55)	(24.03)
$Firm\, size_{i,t}$				-0.092***
				(-25.01)
$Uncertainty_t$		-0.0097	0.093	-0.40***
		(-0.08)	(0.80)	(-3.46)
$Uncertainty_{t-1}$		-0.30***	-0.30***	-0.40***
		(-2.89)	(-3.06)	(-4.10)
Constant	-0.030***	0.048**	0.057**	0.74***
	(-8.86)	(2.03)	(2.54)	(20.51)
Adjusted R^2	0.417	0.417	0.490	0.507
Observations	78149	78149	78149	78149

t statistics in parentheses

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

Notes: The table summarizes firm fixed effects panel regression results using a least square dummy variable (LSDV) estimator. The dependent variable is $Equity\, finance_{i,t}$ for all specifications. All specifications include firm fixed effects. See Appendix A.2 for the detailed definition of firm-level control variables. Numbers in parentheses are t-statistics with adjusted standard errors clustered by firms.

assets of \$3,200 million constant U.S. dollars reduces net stock sales by \$22 million constant U.S. dollars when the measure of uncertainty increases by one standard deviation.

All specifications suggest that equity financing is negatively correlated with cash flow and positively related to Tobin's Q, consistent with the prediction of corporate finance theories discussed above. Sales growth is negatively correlated with equity financing (Spec 3 and Spec 4). The result is in line with the hypothesis that an increase in total sales, controlling for asset growth and cash flow, implies sufficient internal funds that firms are less inclined to rely on external financing. However, a negative correlation between sales growth and net sales of equity is not consistent with Erel et al. (2012), who report a strong positive relationship between sales growth and seasoned equity offerings. The opposite result is mostly due to the inclusion of asset growth. As Erel et al. (2012) do not control for asset growth, the effect of sales growth is confounded with the effect of asset growth. Indeed, the regression results show that asset growth is positively correlated with equity financing. This is consistent with corporate finance theories predicting that internal funds are not fully sufficient to meet the financing needs of fast growing firms, and thus these firms must tap an external source of funds such as debt or equity. Lastly, firm size is negatively correlated with equity financing, which suggests that smaller firms may be more likely to operate at a smaller-than-optimal size, and thus need more funds to reach optimal size.

1.6.3 Robustness

In this section, I show that the empirical results in the previous section are robust to using alternative measures of uncertainty.

As a first exercise, I construct a measure of uncertainty based on firm-level stock returns ($Uncertainty_t^{Stock}$) following Bloom et al. (2012).[21] In particular, I calculate the standard deviation of monthly stock returns across months and firms within a year using CRSP.[22] As Bloom et al. (2012) point out, a stock return-based uncertainty measure has one notable advantage over TFP-based uncertainty measures. The residuals from estimating equation (1.15) are productivity shocks in the sense that they are not forecasted by the regression equation, but this does not necessarily imply that the residuals are not forecasted by firms. In contrast, $Uncertainty_t^{Stock}$ is immune to such concerns. The estimation result is reported in the 1st column of Table 1.8. Stock return-based uncertainty is negatively correlated with equity finance. A one standard deviation increase in $Uncertainty_t^{Stock}$ (0.027) results in an 0.7 percentage point decrease in net stock sales in lags. The statistical and economic significance of $Uncertainty_t^{Stock}$ is similar to other uncertainty measures. Results using a stock return-based uncertainty measure constructed at an industry level ($Uncertainty_t^{Stock-IND}$), reported in the 2nd column, show slightly stronger economic significance. To be more concrete, a one standard deviation in $Uncertainty_t^{Stock-IND}$ (0.028) results in a 1 percentage point decrease in net sales

[21] The correlation between $Uncertainty_t$ and $Uncertainty_t^{Stock}$ is 0.79.

[22] Observations are excluded from the calculation if fewer than 6 months of observations are available per year per firm.

of stock in lags.

As a second exercise, I use the CBOE S&P 100 Volatility Index (VIX_t), which is a widely used proxy of aggregate uncertainty.[23] The result is reported in the third column, and it strongly supports the hypothesis that uncertainty adversely affects equity financing. A one standard deviation increase in the VIX_t (7.1) results in a 1.4 percentage point decrease in net sales of stock contemporaneously, and 0.6 percentage point in lags.

As a third exercise, I investigate if firm size is related to the degree to which uncertainty affects firms' equity financing decisions. This exercise is motivated by Covas and Den Haan (2011), who document that equity financing is significantly procyclical, and that the procyclicality increases as firm size decreases. I introduce interaction terms between uncertainty and firm size, and between real GDP growth and firm size. Results are reported in the first column of Table 1.9. The coefficients of the interaction terms between uncertainty and firm size are positive and significant, which implies that smaller firms' equity financing decisions are more severely and adversely affected by an increase in uncertainty.[24]

As a fourth exercise, I investigate how debt financing is affected by uncertainty. I re-estimate equation (1.16) replacing the dependent variable with $Debt\,finance_{i,t}$, which is changes in total debt normalized by lagged total assets. The result is reported in the second column of Table 1.9. The results suggest that debt financing also decreases as uncertainty increases, and the sensitivity increases as firm size

[23]The correlation between $Uncertainty_t$ andVIX_t is 0.55.

[24]The lagged interaction term between real GDP growth and firm size is negative and significant, which implies that smaller firms' equity financing decisions are more sensitive to the business cycle. This result is consistent with Covas and Den Haan (2011).

Table 1.8: Alternative Uncertainty Measures

	(1) $Equity\, finance_t$	(2) $Equity\, finance_t$	(3) $Equity\, finance_t$
$RGDP\, growth_t$	0.00048	0.0018*	-0.0025***
	(0.48)	(1.79)	(-2.77)
$RGDP\, growth_{t-1}$	-0.0010	-0.0025***	-0.0019**
	(-1.08)	(-2.75)	(-2.22)
$Cashflow_{i,t}$	-0.12***	-0.12***	-0.12***
	(-8.46)	(-8.42)	(-8.60)
$Tobin's\, Q_{i,t}$	0.013***	0.013***	0.013***
	(13.63)	(13.66)	(13.65)
$Sales\, growth_{i,t}$	-0.031***	-0.031***	-0.031***
	(-4.23)	(-4.21)	(-4.26)
$Total\, asset\, growth_{i,t}$	0.15***	0.15***	0.15***
	(24.03)	(24.02)	(24.07)
$Firm\, size_{i,t}$	-0.091***	-0.091***	-0.089***
	(-25.02)	(-24.94)	(-24.88)
$Uncertainty_t^{Stock}$	-0.099		
	(-1.23)		
$Uncertainty_{t-1}^{Stock}$	-0.25***		
	(-3.51)		
$Uncertainty_{j,t}^{Stock-IND}$		0.12	
		(1.58)	
$Uncertainty_{j,t-1}^{Stock-IND}$		-0.35***	
		(-5.21)	
VIX_t			-0.0020***
			(-8.86)
VIX_{t-1}			-0.00081***
			(-3.41)
Adjusted R^2	0.507	0.506	0.508
Observations	78149	78149	78149

t statistics in parentheses

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

Notes: The table summarizes firm fixed effects panel regression results using a least square dummy variable (LSDV) estimator replacing aggregate uncertainty, $Uncertainty_t$, with alternative measures of uncertainty. All specifications include firm fixed effects. See Appendix A.2 for the detailed definition of firm-level control variables. Numbers in parentheses are t-statistics using adjusted standard errors clustered by firms.

Table 1.9: Robustness

	(1) $Equity\,finance_{i,t}$	(2) $Debt\,finance_{i,t}$	(3) $Leverage_{i,t}$	(4) $Equity\,finance_{i,t}$	(5) $Equity\,finance_{i,t}$
$RGDP\,growth_t$	0.0029	-0.020***	-0.014***	0.011***	
	(0.93)	(-7.51)	(-7.35)	(4.05)	
$RGDP\,growth_{t-1}$	0.028***	0.019***	0.017***	0.0035	
	(6.72)	(5.19)	(6.96)	(1.25)	
$RGDP\,growth_t \times Firm\,size_{i,t}$	-0.00056	0.0042***	0.0032***	-0.0018***	-0.0019***
	(-1.28)	(10.67)	(11.43)	(-4.60)	(-4.97)
$RGDP\,growth_{t-1} \times Firm\,size_{i,t}$	-0.0047***	-0.0032***	-0.0027***	-0.00070*	-0.00053
	(-7.95)	(-6.13)	(-7.46)	(-1.79)	(-1.36)
$Cashflow_{i,t}$	-0.14***	0.013	-0.046***	-0.13***	-0.13***
	(-9.56)	(1.06)	(-5.69)	(-8.88)	(-9.15)
$Tobin's\,Q_{i,t}$	0.013***	-0.013***	-0.0089***	0.013***	0.013***
	(13.85)	(-13.83)	(-13.24)	(13.69)	(14.19)
$Sales\,growth_{i,t}$	-0.054***	0.052***	0.042***	-0.042***	-0.044***
	(-7.21)	(6.65)	(8.11)	(-5.69)	(-6.01)
$Total\,asset\,growth_{i,t}$	0.083***	0.084***	0.074***	0.12***	0.12***
	(10.81)	(9.87)	(13.06)	(17.06)	(17.10)
$Firm\,size_{i,t}$	-0.29***	-0.13***	-0.11***	-0.19***	-0.18***
	(-21.21)	(-11.04)	(-16.03)	(-21.00)	(-19.30)
$Uncertainty_t$	-3.84***	-2.82***	-2.56***		
	(-9.12)	(-8.12)	(-11.03)		
$Uncertainty_{t-1}$	-2.30***	-0.27	-0.018		
	(-6.81)	(-0.96)	(-0.09)		
$Uncertainty_t \times Firm\,size_{i,t}$	0.63***	0.61***	0.55***		
	(10.17)	(11.50)	(15.57)		
$Uncertainty_{t-1} \times Firm\,size_{i,t}$	0.32***	0.014	0.051*		
	(6.78)	(0.35)	(1.85)		
$Uncertainty^{IND}_{j,t}$				-1.03***	-1.02***
				(-7.64)	(-7.65)
$Uncertainty^{IND}_{j,t-1}$				-1.20***	-1.13***
				(-9.45)	(-8.94)
$Uncertainty^{IND}_t \times Firm\,size_{i,t}$				0.19***	0.19***
				(9.57)	(9.71)
$Uncertainty^{IND}_{t-1} \times Firm\,size_{i,t}$				0.20***	0.20***
				(10.80)	(10.64)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	No	No	No	No	Yes
Adjusted R^2	0.523	0.191	0.286	0.514	0.520
Observations	78149	78149	78149	78149	78149

t statistics in parentheses

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

Notes: The table summarizes firm fixed effects panel regression results using a least square dummy variable (LSDV) estimator with interaction terms between uncertainty and firm size, and real GDP growth and firm size. The dependent variable of the second and the third column is $Debt\,finance_{i,t}$ and $Leverage_{i,t}$ respectively. See Appendix A.2 for the detailed definition of firm-level control variables. Numbers in parentheses are t-statistics using adjusted standard errors clustered by firms.

decreases. Replacing the dependent variable with $leverage_{i,t}$, which is the ratio between total debt and beginning-of-period total assets, shows a similar result (the third column of Table 1.9). As uncertainty increases, leverage decreases.

As a fifth exercise, I investigate how industry-level uncertainty affects firms' equity financing decisions. This exercise addresses a concern that different industries potentially have a different degree of idiosyncratic productivity dispersion in a given year. The measure of industry-level uncertainty is constructed similarly as in the aggregate uncertainty measure, $Uncertainty_t$, discussed in the previous section. The only difference is that I take the standard deviation of OLS residuals $\hat{u}_{i,j,t}$ of equation (1.15) at the two-digit NAICS level within a year. Hence, industry-level uncertainty, $Uncertainty^{IND}_{j,t}$, varies not only by t but also by industry j. The fourth column of Table 1.9 presents estimation results of equation (1.16) replacing $Uncertainty_t$ with $Uncertainty^{IND}_{j,t}$. Implications are identical to the baseline results reported in Table 1.7. Industry level uncertainty is negatively correlated with equity financing both contemporaneously and in lags, and the results are statistically significant at 1%. In all specifications, I control for the business cycle using contemporaneous and lagged real GDP growth rates. Using industry-level uncertainty allows me to control for the business cycle in an alternative way, which is replacing $RGDP\,growth_t$ and $RGDP\,growth_{t-1}$ with a time fixed effect. This address a potential concern that uncertainty measures are falsely picking up business cycles instead of uncertainty. As the last column of Table 1.9 reports, the inclusion of the time-fixed effect yields an identical conclusion; equity financing is negatively correlated with uncertainty.

1.7 Concluding Remarks

In this research, I study how uncertainty shocks affect firms' financing decisions, in particular equity financing, and how equity finance affects the macroeconomic impact of uncertainty shocks. I build a DSGE model with endogenous debt and equity contracts to investigate macroeconomic consequences of uncertainty shocks working through financial frictions. In my model, firms reduce debt financing in response to increased uncertainty, as debt becomes more expensive due to the increased default probability. This is consistent with the predictions of standard financial accelerator models. The model also predicts a decrease in equity financing in response to higher uncertainty, consistently with the data.

Introducing an endogenous equity contract into a DSGE model is a unique feature of the model, and this feature is important since it affects macroeconomic dynamics in response to uncertainty shocks. Incorporating equity financing generates additional amplification of uncertainty shocks since firms reduce equity financing whenever uncertainty is high. Through this channel, uncertainty shocks are amplified relative to a model with only debt contracts.

By incorporating uncertainty shocks and their amplification through equity financing frictions, my model is also able to explain procyclical debt and equity financing along with countercylical external financing costs, a combination which existing models fail to explain.

I also provide empirical evidence on the relationship between uncertainty and equity financing using firm-level data from Compustat. I show that firms reduce both debt and equity financing in response to higher uncertainty.

I mention two directions for future research. First, it is widely assumed that different classes of firms have varying degrees of financial constraints. Existing research suggests that smaller firms are more sensitive to uncertainty shocks, and my empirical results show that smaller firms' debt and equity finance decisions are more sensitive to uncertainty. However, the model in this paper is silent regarding potential heterogeneity in the effect of uncertainty shocks on equity financing decisions. Future research should model heterogeneous responses of firms' financing decisions to uncertainty shocks.

Secondly, this paper studies mostly uncertainty shocks. Since the financial contract that I propose in this paper can easily be embedded in other representative agent DSGE models, the simple model in this paper can be extended almost immediately to medium/large scale models. In this regard it will also be interesting to see how the equity finance channel affects the economy's responses to other aggregate shocks, such as monetary policy shocks.

Chapter 2: On Corporate Borrowing, Credit Spreads and Economic Activity in Emerging Economies: An Empirical Investigation (coauthored with Julián Caballero and Andrés Fernández)

2.1 Introduction

One of the most important developments in the macroeconomics of emerging market economies (EMEs) since the beginning of the twenty-first century is a major increase in their *corporate* sectors' reliance on foreign debt. The stock of international debt issued by these economies has quadrupled in a little over a decade, from an outstanding stock of debt of about 600 billion USD in the early 2000s to 2.4 trillion USD by the end of 2014.[1] This increase has created an intense debate about the macro implications and desirability of expanded corporate foreign borrowing. A benign view posits that for EMEs, often portrayed as credit-constrained small open economies, access to international capital markets by the corporate sector is essential for sustaining long-run economic growth, as it can provide domestic entrepreneurs with needed funds to finance new investment projects that would otherwise not be

[1] This stylized fact is further documented in Section 2.3 for the 17 EMEs that we consider when computing the stock of international debt.

available from local sources. However, the costly crises of the 1990s and, more recently, the global financial crisis of 2008/2009, have taught us that greater access to capital markets also entails risks for EMEs, particularly stemming from abrupt changes in the amount and the cost of international capital available. This has placed at center stage the role of external financial conditions as important drivers of economic activity in EMEs.

This paper seeks to shed new light on the role that external financial factors play when accounting for economic activity in emerging economies. Our particular interest is to quantify the extent to which changes in the lending conditions faced by the *corporate* sector of EMEs in world capital markets affect economic activity in these economies. For that purpose we build an external financial indicator for several EMEs using individual bond-level data on spreads from corporate bonds issued in foreign capital markets and traded in secondary markets. We then quantify how much information this indicator contains about future fluctuations in economic activity in these economies, and how activity responds to shocks in the indicator. Our focus is on bond issuance because, as we document in detail for 17 EMEs, corporates have preferred this form of finance in recent years when increasing their reliance on international sources of funding.

We find strong evidence that our constructed external financial indicator that we construct contains information on future economic activity in EMEs, even after controlling for other domestic and external factors that may also drive aggregate fluctuations in these economies. Results from panel forecasting regressions indicate that, on average, an increase of 100 basis points in the external financial indicator is associated with a decrease in real output growth of 0.22 percentage points in the following quarter, and up to 0.34 percentage points three quarter ahead. Furthermore, using a panel structural vector autoregressive (SVAR) model, we find that an identified (adverse) shock to the external financial indicator generates a large and protracted fall in economic activity. A one standard deviation shock in the external financial indicator, equivalent to an increase in borrowing costs of 150 basis points, leads to a fall in real output growth of up to 0.75 percent four quarters ahead, and long-run mean growth is reached again only three years after the shock. Furthermore, 35 percent of the forecast error variance in real output growth is accounted for by shocks to the external financial indicator. This number is between two and three times that obtained in previous studies that quantified the role of risk premia shocks for emerging economies' business cycles, but which relied solely on sovereign risk and did not account for the effect of corporate spreads. When looking at other macroeconomic variables, namely aggregate consumption and investment, we find that both react vigorously to shocks to the external financial indicator, with consumption affected more than investment.

These findings are robust to several extensions. First, our benchmark results are virtually unchanged after we control for possible spillovers from sovereign to corporate risk. This is consistent with the fact, also documented, that in recent times new international lending in EMEs has mainly been channeled to the corporate sector, while governments have substituted foreign sources of finance for domestic ones. Second, we show that, while considerably reduced, the information content of our external financial indicator continues to be significant once we control for the VIX, a prominent measure of uncertainty and risk aversion in global capital markets. Third, we find that the predictive power of the external financial indicator considerably increased during the world financial crisis and, more importantly, the post-recovery years. Moreover, its predictive ability continues to hold when we consider bonds issued only by non-financial corporations. Both results are consistent with the fact that, in the post-crisis period, the bulk of the surge in international bond financing by the corporate sector has been done by non-financial corporations. Lastly, we validate our results when using alternative schemes for identification of shocks to our external financial indicator, alternative measures of economic activity, and alternative specifications of the panel SVAR.

This paper is related to and contributes to four different literatures. The stylized facts that we document in terms of the patterns in external financing by EMEs contribute to the work by Shin (2014), Turner (2014) and Powell (2014), among others, on how corporations from emerging economies have stepped up their financing through international capital markets (rather than traditional bank lending). Our work complements this literature by providing a systematic analysis of the external financing patterns exhibited by several EMEs, particularly the large increase by non-financial corporations (NFCs) in international bond issuance.

Our work showing that spreads of international bonds issued by NFCs in EMEs contain information on future economic activity contributes to a long-standing literature that studies the relevance of external financial factors when accounting for aggregate fluctuations in these economies.[2] External financial factors in this lit-

[2]At least since Díaz-Alejandro (1985) the literature has explored how international financial

erature are typically proxied by U.S. interest rates or spreads of EMEs' *sovereign* debt. The papers in this literature usually estimate VAR models that identify the dynamic effects on EMEs' business cycle from exogenous shocks to U.S. interest rates or EMEs' sovereign spreads (see, e.g., the seminal papers by Canova, 2005 and Uribe and Yue, 2006).[3] This literature finds that external financial factors explain a sizeable proportion of business cycles in emerging economies. A recent paper by Akinci (2013), however, shows that the effect of international financial conditions on EME economic activity is driven not by fluctuations in U.S. interest rates, but by risk aversion in global financial markets—as proxied by the volatility of U.S. stock prices—and their effect on sovereign spreads.[4] We contribute to this literature by paying particular attention to the role of *corporate* external borrowing, instead of sovereign borrowing, motivated by the aforementioned shift in the composition of borrowers in foreign capital markets from sovereigns to corporates in EMEs.

conditions affect EMEs. A strand of the literature focuses on the role of capital flows in driving economic conditions or the incidence of crises, either because of surges in inflows (see, e.g., Calvo et al., 1993; Fernández-Arias, 1996; Reinhart and Reinhart, 2009, and Caballero, 2016) or because of sudden stops in inflows (see, e.g., Calvo, 1998 and Calvo et al., 2008). Another strand of the literature studies the effects of international interest rates and global risk aversion on EMEs' business cycles (see references in main text). Our paper contributes to the latter literature.

[3] Several subsequent papers have followed the seminal works of Canova and Uribe and Yue, including the papers by Mackowiak (2007), Agénor et al. (2008), and Österholm and Zettelmeyer (2008). Izquierdo et al. (2008) take a different modelling approach, estimating a Vector Error Correction Model (VECM). Recently, a new vintage of papers using a GVAR approach have studied the global spillovers from U.S. monetary policy, including Chudik and Fratzscher (2011), Chen et al. (2012), Feldkircher and Huber (2016), and Georgiadis (2015). Despite the use of different samples, identifying assumptions and estimation techniques, they all find that external factors explain a sizeable proportion of business cycles in EMEs, ranging from 20 to 60 percent of the variability of economic activity. Neumeyer and Perri (2005) is an early paper showing that sovereign spreads in EMEs behave in a countercyclical manner, which is what subsequent work shows.

[4] The effect of global risk aversion on EMEs' economic fluctuations has also been highlighted by Matsumoto (2011) and Carrière-Swallow and Céspedes (2013); although, these papers are silent on its effect on country spreads. On the effects of global factors on EMEs' sovereign spreads, Arora and Cerisola (2001), González-Rozada and Levy-Yeyati (2008), and Ciarlone et al. (2009) show that EMEs' sovereign spreads depend negatively on global financial conditions, such as U.S. interest rates, U.S. high-yield corporate spreads, and the volatility of U.S. stock prices, respectively.

The empirical work we undertake in this paper in terms of constructing an external financial indicator directly from bond spreads is mostly inspired by Gilchrist et al. (2009) and Gilchrist and Zakrajsek (2012) on the effects of credit market shocks and economic fluctuations in the United States (subsequently extended to Western Europe by Gilchrist and Mojon, 2014 and Bleaney et al., 2016). Our work expands their analysis to the case of EMEs, while simultaneously providing an analysis of the patterns of foreign finance in these economies, which in turn justifies our focus on the international bond issuance by the corporate sector.

The paper is also related to a new vintage of dynamic, stochastic equilibrium models motivated by much of the empirical findings just highlighted. These models aim at accounting for business cycles in EMEs through financial shocks and the amplifying effects of financial frictions for the decisions of private agents (see, most recently, Fernández and Gulan, 2015).[5] Our work contributes to this literature by providing empirical evidence of the hypotheses derived from these models regarding the links between corporate bond spreads and economic activity. Our results offer strong support to the key hypotheses in this literature insofar as external financial factors are a key determinant for economic activity in EMEs through their effect on the corporate sector.

The paper is divided into seven sections, including this introduction. Section 2.2 summarizes the theoretical framework used to think about the links between

[5]This research agenda was initiated by the contributions of Neumeyer and Perri (2005) and Uribe and Yue (2006). Subsequent works include García-Cicco et al. (2010), Fernández-Villaverde et al. (2011), Chang and Fernández (2013), and Fernández et al. (2015a). In a recent theoretical contribution, Chang et al. (2016) study the business cycle effects of the endogenous choice of finance modes for emerging economies.

international borrowing, credit spreads and economic activity in EMEs. Section 2.3 presents the stylized facts on international corporate borrowing in these economies. Section 2.4 describes how we construct the external financial indicator and studies its time series dynamics. Section 2.5 presents our benchmark results in terms of the forecasting information content of the external financial indicator, and the macro dynamics following a shock to it. Section 2.6 presents various extensions and robustness checks. Concluding remarks are presented in Section 2.7. Appendix B includes further technical material as well as further robustness analysis.

2.2 External Corporate Borrowing, Credit Spreads and Economic Activity in EMEs: A Theoretical Framework

Considerable progress has been made in recent years in building microfounded small open economy models that account for the linkages among external financial factors, foreign corporate debt issuance and economic activity in small EMEs. Two clear hypotheses emerge from these works:

1. Spreads on bonds issued by *corporates* of EMEs in international capital markets contain information on aggregate economic activity. Thus, proxies of economic activity in these economies ought to be correlated with these spreads over the business cycle.

2. Exogenous perturbations to these spreads will have an impact on *future* economic activity, mainly via their effect on aggregate investment and consumption.

For the remainder of this section we provide a brief summary of the main insights from the theoretical frameworks developed in recent times that have established a link between external financial factors, foreign corporate debt and economic activity in these economies. The goal is not to provide a comprehensive literature review. Instead, we intend to lay out the main insights from these studies that give rise to the type of empirical tests undertaken in the rest of our work.

The literature has postulated two reasons why agents in EMEs may borrow funds from world capital markets. One is associated with factors that affect the level of aggregate investment. The other relates to factors affecting aggregate consumption. Each one, in turn, articulates a channel through which changes in the financial conditions of such borrowing may have real effects on economic activity.

The first reason, linked to investment, relates to corporates in EMEs facing borrowing needs. Early works in this literature modeled this by assuming that firms borrow in international markets to finance working-capital needs (Neumeyer and Perri, 2005; Uribe and Yue, 2006). This assumption requires firms to hold an amount of non-interest-bearing assets to finance a share of resources devoted to remunerating inputs of production, namely capital and labor.[6] In practice, this assumption drives a wedge between inputs' marginal products and marginal costs. That wedge captures the financial cost associated with the share of resources paid with funds borrowed at interest rate R. Hence, changes to external financial conditions that affect R will be correlated with economic activity in these economies to the extent that financial costs associated with the use of inputs in total production change, driving firms in

[6] Formally, this is often modeled with the restriction that $\kappa_t \geq \eta \left(w_t h_t + r_t^k k_t\right), \;\; \eta \geq 0$, where κ are non-interest-bearing assets, η is the fraction of resources devoted to remunerate inputs of production, wh is the wage bill and $r^k k$ is the amount of resources devoted to renting capital.

EMEs to optimally alter their production and investment levels.[7]

The second reason postulated in the literature as to why agents in EMEs may borrow funds from world capital markets relates to their desire to smooth consumption. It is often assumed that this is accomplished within an environment of market incompleteness where agents in these economies have only the possibility of issuing one-period, non-state-contingent debt in international markets at an interest rate R. Hence, an upward movement in R triggered by changes in foreign financial conditions will be related to a slowdown in economic activity amid a fall in aggregate consumption.[8]

When thinking about R, the (gross) interest rate at which debt with the rest of the world is issued by agents in EMEs, whether for investment and/or consumption needs, the literature has unanimously embraced the small open economy assumption whereby the EME is too small to affect the world interest rate R^*, but a (country-specific) spread, S, may exist over this rate: $R_t = S_t R_t^*$. Hence, movements in R can be traced back to movements in spreads and/or fluctuations in world interest rates. The implicit assumption often used is that there is a large mass of foreign

[7] An alternative way to establish a connection between movements in R and investment decisions is to assume that firms' internal resources may not be enough to achieve the optimal level of capital, in which case they need to resort to issuing debt in international markets (Fernández and Gulan, 2015). In this setup, the resource constraint faced by the average entrepreneur is $q_t k_{t+1} = n_{t+1} + d^f_{t+1}$where k is the stock of capital purchased at price q; her net worth is n; and d^f is the stock of debt issued in international markets at an interest rate R. Hence, changes to external financial conditions that lead to upward movements of R will be correlated with a slowdown in economic activity amid an investment slump, as entrepreneurs purchase less capital to produce final goods.

[8] This can be modeled by assuming a sequential budget constraint of a typical consumer as $c_t = d^h_t - R_{t-1} d^h_{t-1} + w_t h_t$, where d^h_t is the stock of (one period, non-state-contingent) debt issued in period t and due in the next period, and c is the amount of consumption. The negative correlation between changes in R and c could also be seen through the intertemporal Euler condition for consumption, which relates present and future consumption, and interest rates.

investors willing to lend to the emerging economy any amount at rate R_t. Loans to the EME are risky assets because there can be default on payments to foreigners. Time variation in this risk is captured by fluctuations in S_t. Variation in R_t^* account for changes in the risk aversion of foreign lenders/investors or movements in global monetary/fiscal policies. This does not preclude the possibility that R^* and S are correlated. In fact, it can be the case that global events that affect the former (i.e., monetary or fiscal policy announcements in the United States) percolate into the risk appetite of foreign investors for emerging market bonds, thereby affecting their spreads, as has been empirically quantified (see Uribe and Yue, 2006).

When modeling the behavior of spreads (S) several alternatives have been considered in the literature. The most agnostic and reduced-form approach has been to estimate a process for spreads by simply regressing them on (lagged) country "fundamentals" such as output, investment, the trade balance and white noise perturbations, in the context of SVAR models (Uribe and Yue, 2006; Akinci, 2013). An alternative semi-structural approach has been to directly postulate a link between spreads and (latent or observed) country fundamentals included in the structural model such as future expected productivity or the price of commodities exported by the EME and then calibrate (or estimate) such linkages within the context of the calibration (or estimation) of the full-blown dynamic general equilibrium model (Neumeyer and Perri, 2005; Chang and Fernández, 2013; Fernández et al., 2015a). This captures the idea that productivity and/or commodity prices contain information on the creditworthiness of the borrower EME to the extent that they are a determinant of its repayment capacity.[9] Lastly, other studies have resorted to a full structural approach where S is endogenous to the financial contract stipulated between domestic borrowers and external investors (Fernández and Gulan, 2015). Under this approach, a financial accelerator endogenously generates a spread process that depends upon financial variables, namely entrepreneurial leverage. Hence domestic or external shocks that affect the value of entrepreneurs' net worth will influence spreads.[10]

Summing up, spreads on corporate bonds issued by firms in emerging market on international capital markets ought to contain information on future economic activity in these economies. Thus one would expect economic activity in EMEs to be correlated with spreads over the business cycle. Moreover, perturbations to these spreads that are orthogonal to current economic activity ought to have an impact on *future* activity, mainly via their effect on aggregate investment and consumption.

In what follows we will formally explore the empirical validity of these hypotheses, first by constructing an external financial indicator that serves as proxy for the behavior of S in several EMEs, using micro level data on international bond

[9]Formally, what has often been done is to postulate some *ad hoc* reduced-form equation within the structural model whereby spreads react to other variables inside the model, e.g., $S_t = \widetilde{\eta}_1 E_t TFP_{t+1} + \widetilde{\eta}_2 E_t P^{co}_{t+1} + \varepsilon_t$, where TFP_{t+1} and P^{co}_{t+1} capture future productivity and commodity prices; ε_t are exogenous and country-idiosyncratic perturbations to spreads; and the $\widetilde{\eta}$'s are reduced-form parameters that capture the elasticity of spreads with respect to these variables and are either estimated or calibrated to match some empirical regularities. Default decisions are not directly modeled in this approach. The implicit and simplistic assumption made is that, as in Kehoe and Perri (2004), private domestic borrowers always pay their obligations in full but that in each period there is a probability that the local government will confiscate all interest payments going from local borrowers to the foreign lenders. Fluctuations in the confiscation probability in a particular economy are captured by the above equation, albeit in a reduced form.

[10]Formally, this is obtained by deriving the function $S(\bullet)$ which maps the value of net worth to spreads, e.g., $S_t = S(q_t k_{t+1}/n_{t+1})$, where qk is the market value of assets held by entrepreneurs in EME and n is their equity. It is derived that $S'(\bullet) > 0$, which then implies that highly leveraged entrepreneurs, when faced with a positive windfall (e.g., a boost in productivity), will de-leverage on the margin, hence driving interest rates down and generating countercyclical interest rates.

issuance by the corporate sector in these economies. We will then quantify the degree of comovement between this index and economic activity. Finally, we will measure the extent to which identified shocks to this indicator generate macroeconomic fluctuations in these economies. Before doing this, however, in the next section we begin by documenting recent trends in access to international capital markets by the corporate sector in EMEs.

2.3 External Corporate Borrowing in EMEs: Stylized Facts

The relevance of international financial factors for economic activity in emerging markets hinges, to a large extent, on the reliance on foreign debt by the corporate sector in these economies. This section documents the considerable increase in access to international capital markets, in particular through bond market, by the corporate sector of 17 EMEs since the turn of the century.[11]

2.3.1 Sample of Countries and Data

When selecting the pool of EMEs to study we use three filters. First, we select all economies that have been included in the most recent peer-reviewed studies of EMEs' business cycles, or that have been classified as emerging economies by multilateral organizations or rating agencies.[12] Second, we remove from this list

[11]The stylized facts that we document in terms of the patterns in external financing by EMEs complement work by Shin (2014), Turner (2014) and Powell (2014) on how corporations from emerging economies have stepped up their financing through international capital markets. A recent paper by Gozzi et al. (2015) documents key characteristics of corporate bonds market in EMEs.

[12]The academic studies that we use are Neumeyer and Perri (2005), Uribe and Yue (2006), Aguiar and Gopinath (2007), Fernández and Gulan (2015), and Fernández et al., 2015a. The multilateral organizations and rating agencies that we look at are i) the IMF; ii) MSCI; and iii)

those countries where there was at least one episode of sovereign default since the year 2000, as these may have caused important disruptions in the access to foreign capital markets by the corporate sector. Third, we discard those countries that have had a history of high pervasive capital controls.[13] This process leaves us with a total of 17 EMEs that can be split into four geographical regions:[14]

(i) Latin America: Brazil, Chile, Colombia, Mexico and Peru.

(ii) East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand.

(iii) Eastern Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey.

(iv) Other Regions: South Africa and Israel.

For each of these economies we construct quarterly measures of corporate debt in international capital markets. We use data on stocks and flows of corporate debt. For stocks we use the data reported by the Bank of International Settlements (BIS). For flows, or gross issuance, we construct a measure of new bond issuance using information on the universe of bonds reported by Dealogic DCM, a leading data provider that tracks global debt capital markets. We choose the period 2000-2014

JPMorgan.

[13] We use the recent index on *de jure* measures of capital controls by Fernández et al. (2015b), which provides a quantitative measure of the existence of capital controls in both inflows and outflows separately, across various asset categories, for 100 economies between 1995 and 2013. The index is defined to be between zero (absence of controls in all asset categories) and one (controls in all categories). We define a country as having had a history of high capital controls if the average index over the 19 years is more than one and a half standard deviations above the median across countries.

[14] Out of a total of 21 EMEs identified in the first filter, Argentina and Ecuador were removed from the initial pool of economies as they experienced episodes of sovereign default within the period analyzed (second filter). China and India were not considered because they surpass the threshold of capital controls defined earlier (third filter).

for our analysis to be consistent with the period where available data on corporate bonds spreads exists, and that we later analyze.

2.3.2 Stylized Facts

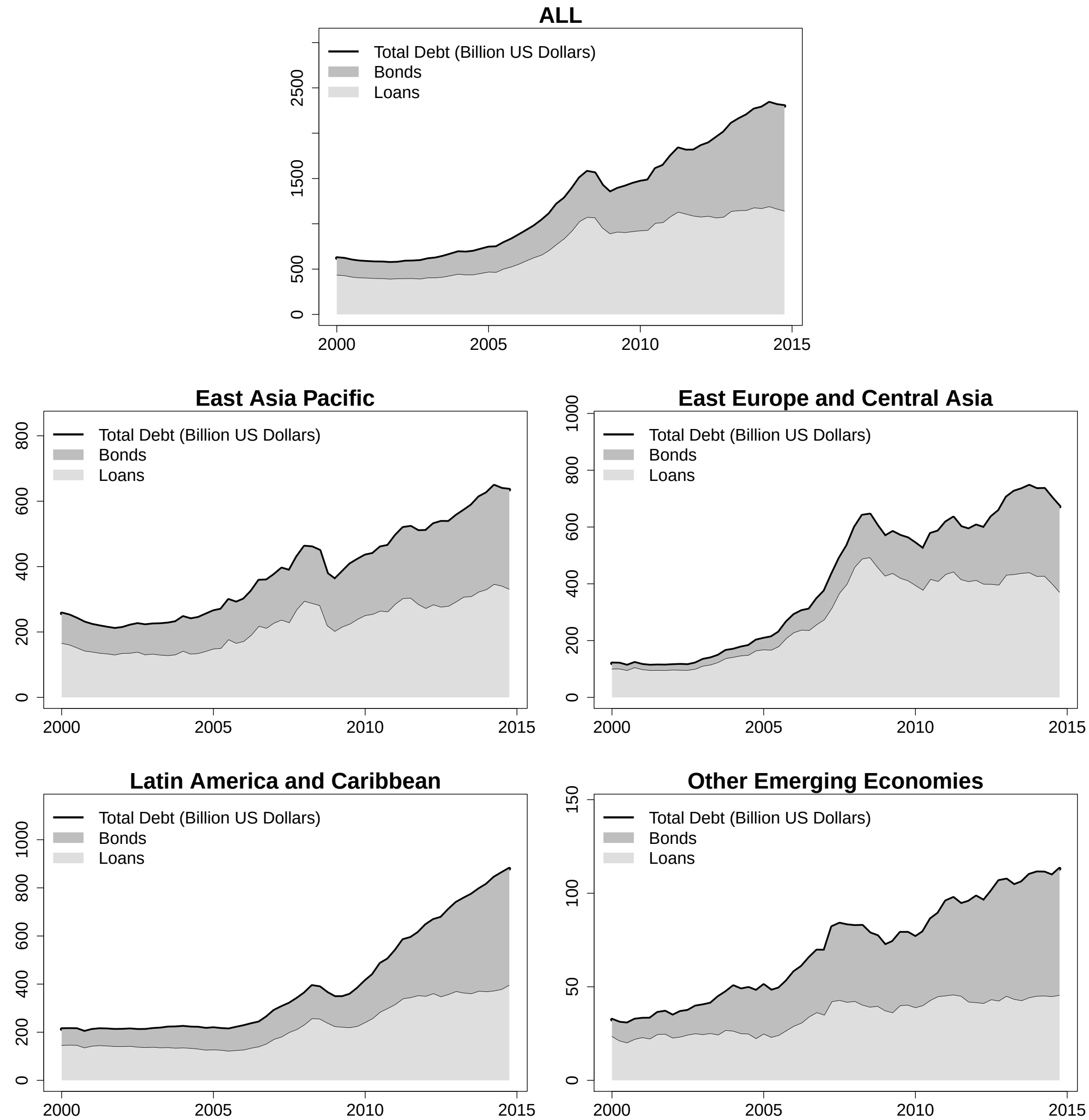
The total stock of international corporate debt is presented in Figure 2.1. We disaggregate the stocks between debt coming from international bond issuance and that associated with cross-border bank loans. The upper plot aggregates debt across all 17 EMEs considered, while the remaining four plots disaggregate the numbers across the four geographical regions mentioned above. The numbers reported are in current USD Billions. The data are taken from information on the BIS' website and is collected on a nationality basis.[15] The stock of bond debt aggregates non-financial corporates, banks and other financial institutions and excludes sovereign bond issuance by construction. The stock of loan debt includes banks and non-banks.[16]

The most salient stylized fact from Figure 2.1 is the considerable increase in the stock of debt issued by EMEs' corporations since the early 2000s, which quadrupled

[15]The nationality of a bond is based on the location of an issuer's ultimate parent company, while the residence of a bond is based on the location of the immediate issuer of a security. For example, if a subsidiary of a Korean firm operating in the U.S. issues a bond, it is considered a U.S. bond by residency, and a Korean bond by nationality. Shin (2014) and Turner (2014), among others, suggest that debt on a nationality basis is more accurate than on a residence basis due to the increase of debt issues by offshore affiliates of corporates in emerging markets.

[16]Although BIS data on cross-border bank loans do not decompose the stock of loans into private sector and government, we assume in Figure 2.1 that cross-border bank loans to sovereigns of EMEs are negligible. We double-checked this assumption based on data collected from national sources for the largest five Latin American economies and found that for the period 2006-2014 the mean ratio of cross-border loans made to governments to total cross-border loans was less than 1% (see Table B.1 in Appendix B.2). In countries with higher levels of development of local bond markets, such as Chile and Mexico, this figure is 0%. We feel it is safe to assume that this pattern is also found in other emerging economies. Lastly, geographical aggregation of debt does not net out debt with other EMEs in the sample.

Figure 2.1: Stock of Private Sector International Debt in EMEs by Region



Notes: This figure shows the aggregate stock of private sector international debt for 17 emerging economies (EMEs), decomposing the outstanding stock into cross-border bank loans and international debt securities (bonds). The stock of securities is on a nationality basis. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

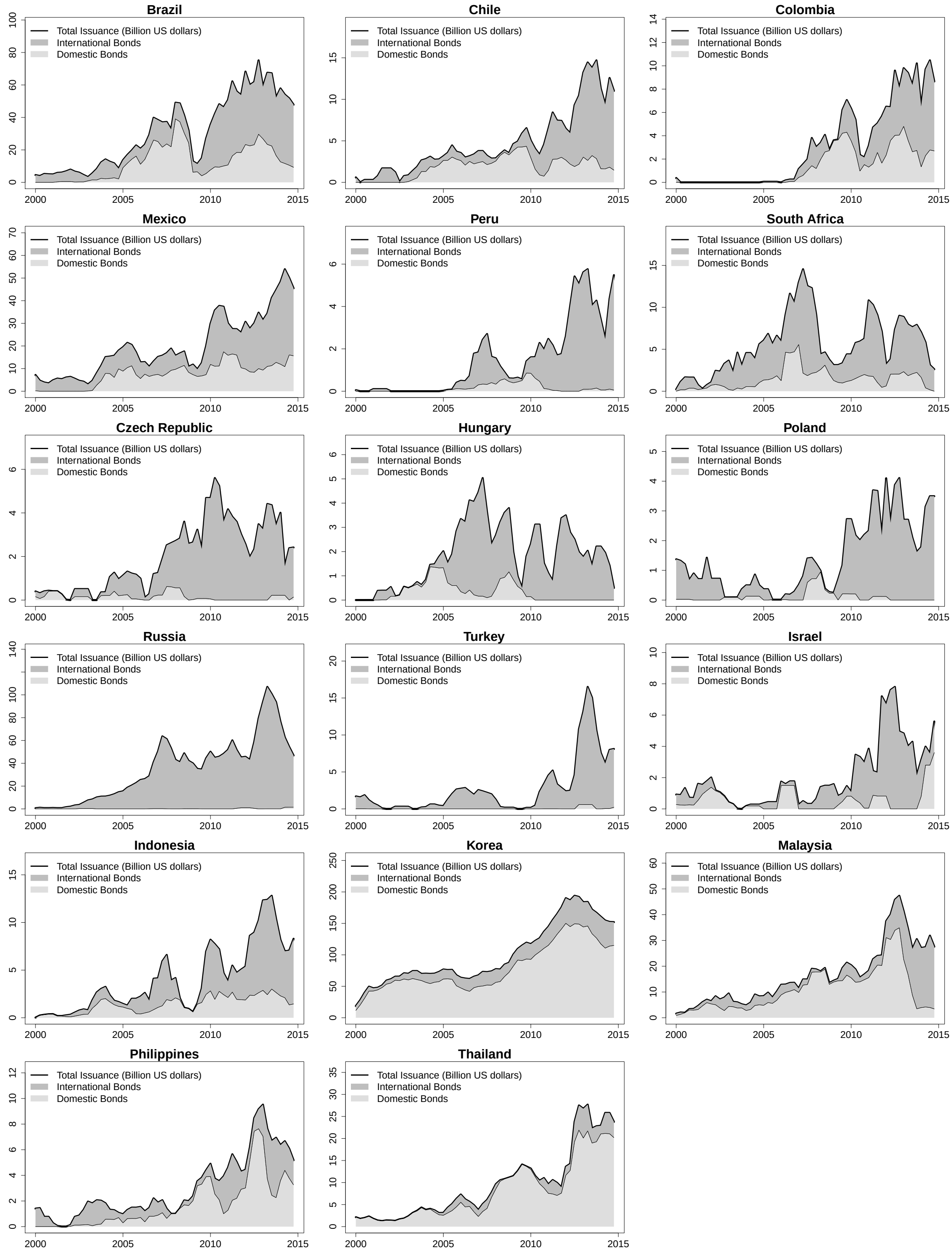
from an initial level of about 600 billion USD to 2.4 trillion USD by the end of 2014. The sharpest increase started in the mid-2000s and suffered a reversal during the onset of the Global Financial Crisis in 2008. That reversal was short-lived, however, and the accumulation of debt continued with a vigorous pace afterwards. The other remarkable stylized fact that emerges from Figure 2.1 is that the lion's share of this recent increase in corporate debt comes from bond issuance. Debt from loans also increased, but less proportionately than that from new bond issuance. Finally, it is also remarkable that these two stylized facts hold across all four geographical regions considered.

Given the relative importance of bonds in the accumulation of debt in EMEs, we turn to a closer look at bond issuance in Figure 2.2. It documents the value of total corporate bond issuance over the sample period, in current U.S. dollars, for each of the 17 EMEs considered. The figure divides gross bond issuance on a nationality basis into domestic and international issuance. Aggregation is done using transaction-level data for all bonds available.[17] Again, the most salient stylized fact that comes out of Figure 2.2 is that corporate bond issuance has increased considerably since the early 2000s across all EMEs considered and, importantly, the lion's share of this increase comes from bonds issued in international markets. Even though this trend started before the onset of the global financial crisis, most of the expansion occurred afterwards.

In all Latin American countries there is a tendency for both domestic and international bond issuance to increase since the early 2000s, but the trend post-crisis accelerates most vigorously in the latter. In turn, the dominance of international

[17] Appendix B.1.1 contains further details on the criteria used when determining if a bond is issued in foreign capital markets, and other details of the dataset. It also documents how the stylized facts are, to a large degree, robust to measuring international bond issuance on a residence basis.

Figure 2.2: Corporate Gross Bond Issuance in EMEs by Country



Notes: This figure shows gross issuance of international and domestic debt securities (bonds) by country on a nationality basis. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See the Appendix for a description of how the country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

issuance is much more marked for Eastern and Central European countries, where issuance of domestic debt is virtually non-existent in most of the countries. This contrasts with the case of most East Asian countries in our sample, where domestic issuance accounts for the largest share. Nonetheless, for all countries in this region we also observe a tendency for international issuance to increase its share, particularly in the post-financial crisis period.

There are four additional stylized facts related to the issuance of debt securities in EMEs that we summarize here but further document in Appendix B.2 for the sake of space. First, by and large, international bond issuance has been a corporate phenomenon, as sovereigns in EMEs have instead substituted foreign for domestic financing.[18] Second, the increase in international bond reliance by the corporate sector has taken place with roughly the same strength in both financial and non-financial corporations.[19] Third, the vast majority of international bond issuance is denominated in foreign currency, most of which is denominated in U.S. dollars (more than 60 percent, on average) or other non-local currency (20 percent). Fourth, the increase in foreign bond issuance by corporates in EMEs exceeds the recorded growth in economic activity in the post-financial crisis period observed in these economies. The ratios of gross bond issuance to GDP increased in most countries considered, particularly since the onset of the global financial crisis.[20]

[18] A proper analysis of sovereign debt is beyond the scope of this paper. However, it ought to be noted that this trend in sovereign bond issuance should not be taken as evidence that sovereigns are more insulated from external financial shocks since, in some countries, international investors are the majority holders of this locally-issued, locally-denominated debt.

[19] This is in line with the recent work of Cortina-Lorente et al. (2016), who document that 50 percent of bond issuance in developing countries is done by financial firms.

[20] Latin America, for example, had similar shares of gross bond issuance in both domestic and international securities by 2008, on the order of 1 percentage point of GDP. By the end of our

Summing up, the systematic analysis of a pool of 17 EMEs reveals that bond issuance by corporations in these economies grew at a fast pace after the turn of the century, mostly driven by issuance in foreign capital markets. This trend accelerated after the Global Financial Crisis, and it was concentrated in bonds denominated in foreign currency, mainly USD, outpacing growth in other external sources of finance such as direct bank loans. This has led the stock of debt issued by corporates in these EMEs to quadruple in little over a decade. In particular, in the four geographical regions defined earlier, gross international corporate bond issuance as a share of GDP has increased from 0.95% to 2.4% in East Asian and Pacific, 0.52% to 3.53% in Eastern Europe and Central Asia, 0.88% to 2.09% in Latin America, and 0.34% to 1.58% in other regions between 2000Q1 and 2013Q2. Sovereigns, unlike corporates, have moved away from issuing bonds in international markets and have relied more on domestic markets as shown in Figure B.5.

2.4 An External Financial Indicator of Credit Spreads on Corporate Bonds in Emerging Economies

2.4.1 Constructing an External Financial Indicator

We now describe the methodology and data sources that we use to construct an external financial indicator for emerging economies based on the bonds issued by their corporate sectors in international markets. We focus on these bonds since

sample, in 2014, this had tripled for the case of international bonds, while it remained constant for domestic ones.

our goal is to capture international financial forces that affect economic activity in these economies.

We construct the external financial indicator for emerging economy k at quarter t (EFI_t^k) by taking a weighted average of option-adjusted spreads (OAS) across a sample of bonds issued by the corporate sector of economy k. The concept of OAS is suitable for our purpose because it provides a way to homogenize spreads across a variety of bonds of different characteristics.[21] Formally:

$$EFI_t^k = \sum_i w_{it}^k s_{it}^k \tag{2.1}$$

where s_{it}^k is the OAS for bond i at time t and w_{it}^k its relative weight. The latter is computed as

$$w_{it}^k = \frac{Bond\,Size_i^k}{\sum_{j=1}^{NB_t^k} Bond\,Size_j^k} \tag{2.2}$$

where NB_t^k denotes the number of bonds issued by the corporate sector in economy k whose OAS is available at time t, and $Bond\,Size_i^k$ refers to the size of bond i measured in constant USD.

Because Dealogic, our data source for bond issuance presented in the previous

[21] The terminology "option" originally refers to the callability or puttability of the bond. The concept of OAS is introduced to account for a potential stop of cash flow as a result of call and put options being exercised. It also takes into account default risk since all possible future states of cash flow are considered in calculating OAS. Formally, let r_t and $r_t^{i,k}$ denote, respectively, the (time varying) yield curves of the safe asset and the bond i in economy k, so that $s_{it}^k = r_t^{i,k} - r_t$. An OAS, s_{it}^k, is computed after deriving $r_t^{i,k}$ as a solution to the following equation (omitting the k index for simplicity)

$$p_t^i = \sum_{n=1}^{N} \prod(n) \sum_{\tau=t}^{M} \frac{C_\tau^i(n)}{(1 + r_\tau + r_t^i)}$$

where p_t^i is the bid price of the risky bond i; $\prod(n)$ denotes the probability of n^{th} path of the economy being realized; M stands for maturity; and $C_\tau^i(n)$ denotes the cash flow in the path n. See O'Kane and Sen (2005) and Gabaix et al. (2007) for further explanations on the OAS.

section, lacks information on OAS, we switch to Bloomberg when computing the external financial indicator. This data provider contains OAS for a large pool of bonds issued by corporates in emerging market economies since the late 1990s. When choosing the sample of bonds to use in computing the external financial indicator we follow a set of criteria. Among the universe of corporate bonds available in Bloomberg, we choose only those with at least one observation for OAS at a quarterly frequency over their lifetime. We also drop bonds from the sample if information is not available on either date of issuance, bond size, industry that the issuer belongs to, maturity date, or currency of denomination. Among this pool of bonds, we focus only on USD-denominated corporate bonds that have been issued in foreign capital markets.[22,23]

After dropping outliers (top and bottom 0.5 percentiles of OAS for the entire sample of bond-quarter observations by country), we are left with a total of 2,339 bonds and 23,791 (unbalanced) bond-quarter observations for the period 1999.Q2-2013.Q2 and across seven emerging economies: Brazil, Chile, Korea, Mexico, Malaysia, Peru and Philippines. Among the countries considered in the previous section, these were the ones for which at least one bond was observed for every quar-

[22]Due to lack of information on governing law and listing place for each bond in our Bloomberg terminal, we used information on ISIN and issuer's country of incorporation to make sure that we kept only international debt securities in our sample. See Appendix B.1.1 for details on the definition of international debt securities we use.

[23]Even though Bloomberg does not allow us to download data on the specific treasury used for the OAS computation, we manually checked the Bloomberg screen for a selected number of bonds and found that in all cases with available data it is a U.S. Treasury. We manually checked bonds for all possible combinations of issuer's country of incorporation, country where the bond ISIN was assigned, and type of exchange where the bond is listed (unlisted or international, the latter defined as an exchange different from the issuer's country of incorporation). We checked a total of 54 different bonds, which is the total number of combinations in our data. In all cases with available data the specific treasury used for the OAS calculation was a U.S. Treasury (seven bonds did not have information available).

ter in the sample (we assigned countries based on issuer's country of incorporation).

The summary statistics of the dataset used to construct the external financial indicators are presented in Table 2.1. The average number of bonds per quarter across all countries is just under 400, and differs between countries. Brazil, Mexico, Korea and Chile exhibit the largest shares of the bonds considered, ranging between 185 to 1,061 bonds. In contrast, Malaysia, Peru and Philippines, have less than a hundred different bonds. In all countries, the number of bond-quarter observations remains stable until 2009 and then increases until the end of the sample (not reported).[24]

The size of bond in Table 2.1 refers to total proceeds (i.e., the dollar amount raised by the firm by issuing the bond). The average size is $329 million but the size distribution is highly (positively) skewed, akin to that documented in Gilchrist and Zakrajsek (2012) for U.S. corporate bonds. Maturity at issue and terms to maturity respectively represent years left to maturity at issue date and at the observation date. The mean is close to seven years for both variables. On average, these are two to three years shorter than the case for the U.S. reported in Gilchrist and Zakrajsek (2012). Arguably, this reflects the ability of U.S. firms to issue bonds at longer maturities than firms in EMEs, and it also echoes the findings of Broner et al. (2013) who document that EMEs tend to borrow short term.

The mean OAS spread is 370 basis points (bp) for the sample period, and it is positively skewed, with a large standard deviation of 420 bp. The same pattern is

[24]Figure B.8 in Appendix B.2 presents evidence that the subsample of bonds with OAS data is representative of the universe of bonds studied in Section 2.3.

Table 2.1: Dataset on Corporate Bond Spreads from Emerging Economics: Summary Statistics

Country	N. Bonds	N. Obs.	Statistics	Mean	SD	Min	Median	Max
All Countries	2339	23791	Number of bonds per quarter	394.96	201.92	176.00	324.00	1153.00
			Size of bond ($ mil)	329.30	375.58	0.10	236.12	3037.77
			Maturity at issue (years)	6.94	7.54	0.08	5.50	100.08
			Term to maturity (years)	6.48	8.19	0.00	4.50	96.25
			OAS spread (basis point)	370.52	420.93	27.24	254.94	5685.23
Brazil	1061	6666	Number of bonds per quarter	116.95	72.11	57.00	92.00	509.00
			Size of bond ($ mil)	183.18	291.15	0.10	68.71	1814.23
			Maturity at issue (years)	3.93	4.07	0.08	2.00	30.00
			Term to maturity (years)	3.84	3.54	0.00	2.75	30.25
			OAS spread (basis point)	471.29	510.36	33.50	342.90	5685.23
Chile	185	3186	Number of bonds per quarter	55.89	30.84	14.00	51.00	132.00
			Size of bond ($ mil)	416.61	218.31	4.71	406.82	1185.77
			Maturity at issue (years)	11.68	11.13	1.00	10.00	100.08
			Term to maturity (years)	8.65	10.35	0.00	6.50	96.25
			OAS spread (basis point)	249.33	143.52	27.24	229.28	1497.09
Korea	390	5170	Number of bonds per quarter	90.70	52.60	35.00	78.00	221.00
			Size of bond ($ mil)	395.44	309.93	4.20	347.65	2053.47
			Maturity at issue (years)	6.74	6.93	0.50	5.00	100.00
			Term to maturity (years)	5.57	8.08	0.00	3.75	93.25
			OAS spread (basis point)	209.78	130.03	36.18	186.43	1017.10
Malaysia	79	1704	Number of bonds per quarter	29.89	7.16	9.00	31.00	41.00
			Size of bond ($ mil)	704.04	580.43	59.76	524.15	3037.77
			Maturity at issue (years)	13.45	15.64	2.00	10.00	100.00
			Term to maturity (years)	10.75	14.98	0.00	6.50	95.25
			OAS spread (basis point)	211.67	203.68	37.64	177.09	2495.75
Mexico	485	5477	Number of bonds per quarter	96.09	43.67	51.00	77.00	211.00
			Size of bond ($ mil)	493.93	477.60	0.19	333.77	2963.59
			Maturity at issue (years)	10.00	6.56	0.75	9.50	32.00
			Term to maturity (years)	7.71	6.59	0.00	6.25	32.00
			OAS spread (basis point)	507.95	569.53	27.90	333.59	5415.02
Peru	60	310	Number of bonds per quarter	5.44	10.10	1.00	1.00	52.00
			Size of bond ($ mil)	380.66	198.62	70.44	307.34	800.44
			Maturity at issue (years)	9.12	3.35	3.50	10.00	25.00
			Term to maturity (years)	7.36	3.42	0.75	7.38	25.00
			OAS spread (basis point)	430.75	256.92	84.28	347.20	1496.38
Philippines	79	1278	Number of bonds per quarter	22.42	4.57	14.00	22.00	31.00
			Size of bond ($ mil)	336.25	243.70	113.35	274.86	1184.59
			Maturity at issue (years)	10.38	11.58	2.00	8.50	100.00
			Term to maturity (years)	7.32	8.95	0.00	5.00	88.50
			OAS spread (basis point)	405.47	219.87	55.16	356.61	1998.70

Notes: This table reports summary statistics of the bonds in our dataset. The columns N. of Bonds and N. of Obs. report the number of bonds and the number of OAS-quarter observations in the sample for each country for the entire sample period of 1999.Q2-2013.Q2, respectively. Number of bonds per quarter refers to the number of bonds with an OAS observation at a given quarter. Size of bond is measured in real U.S. dollars (2010.Q3 = 100). OAS spread is the option-adjusted spread of a bond in basis points at a given quarter. Maturity at issue refers to the remaining years of a bond from its issuance date to its maturity date. Terms to maturity refers to the remaining years of the bond from a given quarter to its maturity date. We exclude from the sample OAS observations that are below (above) the country-specific 0.5^{th} (99.5^{th}) percentiles of OAS-quarter observations of all USD denominated bonds available in Bloomberg for the country (including sovereign bonds).

observed across all seven countries in the sample, although considerable differences in the average OAS can be seen. Mexico and Brazil are the countries with the highest average OAS, 508 bp and 471 bp, respectively, while Chile (249 bp) and Korea (210 bp) exhibit the lowest levels, nearly half of those in Brazil and Mexico.

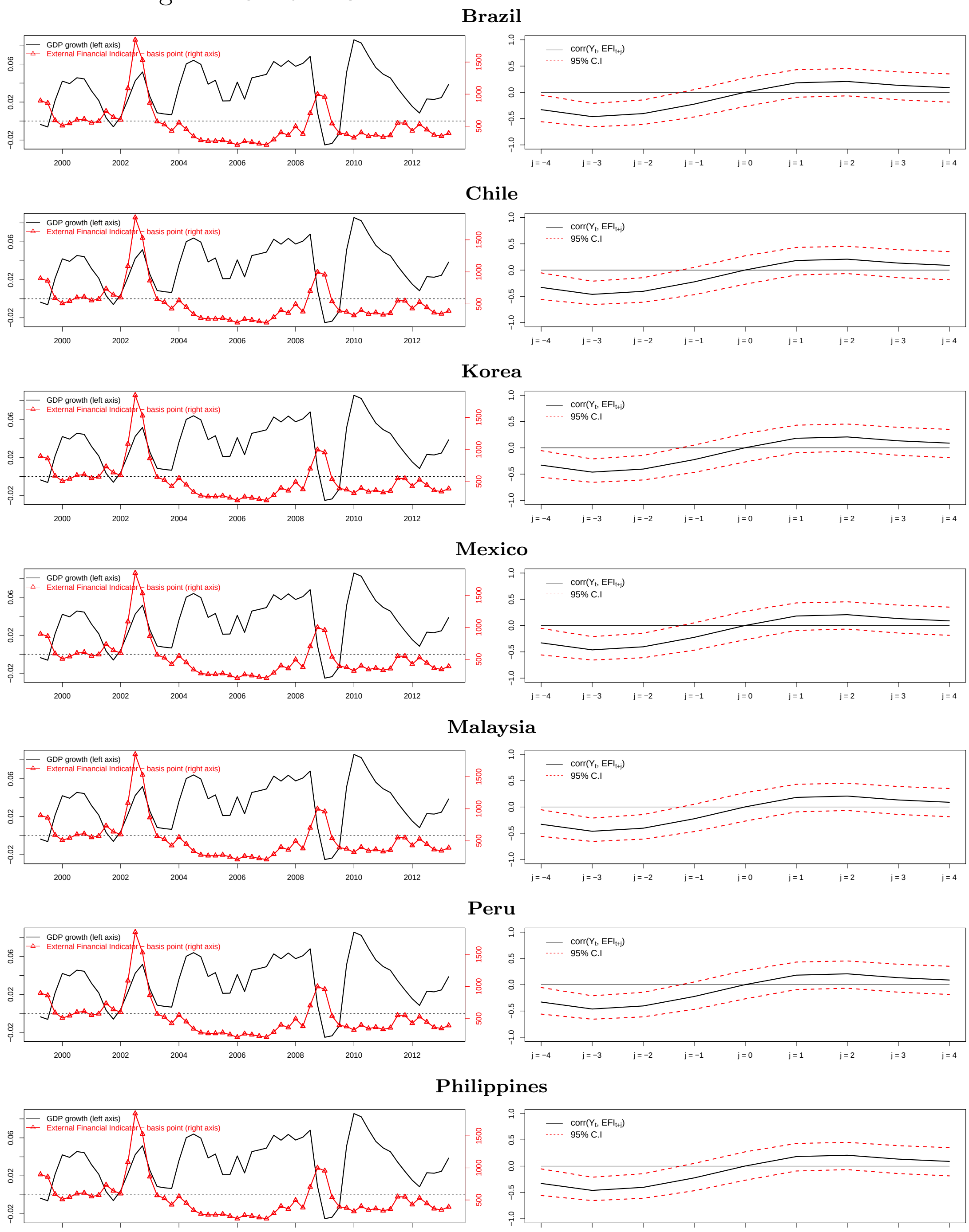
2.4.2 Dynamics of the External Financial Indicator

We now document the time series dynamics of the external financial indicators constructed, paying close attention to their comovement with real economic activity. The left column in Figure 2.3 plots, for each of the seven countries considered, the time series of EFI together with real annual GDP growth, during the sample period 1999.Q2-2013.Q2. The two variables exhibit negative comovement. This pattern is most evident during the fall in economic activity around the global financial crisis of 2008/9 and the subsequent recovery. The crisis period was characterized by spikes in all the EFIs. It is also noteworthy that our series of EFI fell to near pre-crisis levels as the EMEs in the sample recovered from the crisis. The negative comovement is also observed before the crisis in most countries, when these economies experienced sustained economic growth for several years while simultaneously our measure of EFI displayed long and protracted reductions.[25]

The degree of cyclicality of our measures of EFI is further assessed by computing their unconditional serial correlation with real GDP growth: $corr\left(\Delta GDP_t^k, \Delta EFI_{t+j}^k\right)$ for $j = -4, -3, ..., 4$; where ΔGDP_t^k is real annual GDP growth in economy k and

[25] Peru is a notable exception, though. This country's EFI remained flat for most of the episode prior to the crisis of 2008/9. This could partly reflect the lack of a well-established market of foreign bonds in this country during this period, as was documented in the previous section.

Figure 2.3: Real GDP and the External Financial Indicator



Notes: These figures show the time series dynamics of the external financial indicators (EFI) we construct for each country in our sample with corporate spreads data and their comovement with real economic activity. The left column presents the time series of EFI in levels (diamond/red) and of the annual real GDP growth rate (solid/black), both at a quarterly frequency. The right column presents the correlation between real GDP growth and changes in EFI at different lags $(corr\,(\Delta GDP_t,\, \Delta EFI_{t+j}))$ for $j = -4, \cdots, 4$. Red dotted lines represent a 95% confidence interval. The sample period is 1999.Q2-2013.Q2.

ΔEFI^k_{t+j} is the (annual) first difference in EFI^k. The results of this exercise are reported in the right column of Figure 2.3. They indicate that EFI is a leading indicator of economic activity, as the correlation exhibits its trough when $j < 0$,, i.e., economic activity today co-moves the most, and in opposite direction, with lagged changes in EFI.

Lastly, it is worth noting that the EFIs exhibit a strong comovement among themselves. In fact, the first principal component of the seven indicators accounts for 73 percent of the sample variance. Likewise, growth in the emerging markets considered also exhibits strong comovement: 65 percent of the sample variance is associated with the first principal component. We interpret this as evidence that EFI captures global financial forces that affect real economic activity in emerging economies. Later we will formally test this interpretation.

2.5 The External Financial Indicator and Economic Activity

The evidence presented so far is consistent with the hypothesis that spreads on bonds issued by *corporates* of EMEs in international capital markets have information on aggregate economic activity which would explain the negative comovement observed between the two variables over the business cycle. We turn now to a more formal analysis of this hypothesis by quantifying the information content and predictive ability of credit spreads of these bonds on economic activity. We will also evaluate the hypothesis that exogenous perturbations to these spreads have an impact on *future* economic activity.

2.5.1 Forecasting Information Content of the External Financial Indicator

When assessing the information content and predictive ability of credit spreads of corporate bonds issued in international markets for economic activity in emerging economies, we extend Gilchrist and Zakrajsek's (2012) forecasting specification to a multi-country panel setting. Formally, we estimate a dynamic balanced panel regression of real GDP growth against changes in EFI:

$$\Delta GDP^k_{t+h} = \alpha_k + \sum_{j=0}^{p} \beta_j \Delta GDP^k_{t-j} + \gamma \Delta EFI^k_t + \Gamma \Omega_t + \widetilde{\Gamma}\widetilde{\Omega}^k_t + \epsilon_{k,t+h}, \text{ for } h \geq 1 \quad (2.3)$$

where k denotes each of the seven emerging economies considered, $k = 1, ..., 7$; and $h \geq 1$ is the forecast horizon. In our benchmark specification we fix $h = 1$, but later consider alternative values. Variables ΔEFI and ΔGDP are annual changes in EFI and the (log of) real GDP, respectively.[26] We set the lag length equal to one ($p = 0$), although we later explore a richer lag specification structure as a robustness check. The estimation period starts in 1999.Q2, when our EFI series begin, and ends in 2013.Q2.

We estimate the dynamic panel regression with country fixed effects (α_k) and use sets of controls that are country-specific ($\widetilde{\Omega}^k$) and global (Ω). The choice of controls is motivated by the literature on drivers of economic activity in emerg-

[26] We will refer to annual real GDP growth and ΔGDP interchangeably from now on.

ing economies (see the Introduction). In particular, guided by previous studies on the role of global factors when accounting for economic activity in EMEs, we include in Ω two variables that are common across the seven countries and that aim at capturing the role of foreign factors beyond those already captured in changes of EFI: (annual) changes in term spreads of 3-month and 10-year U.S. Treasury yields, $\Delta USYield\,Curve$, and (annual) changes in the real U.S. Federal Funds Rate, ΔRFF_t.[27] These two were included in Gilchrist and Zakrajsek's (2012) original specification for the U.S. economy as domestic controls. In terms of the country-specific controls, we include in $\widetilde{\Omega}^k$ a measure of the domestic monetary policy stance by including the (annual) change in the policy rate in real terms, $\Delta RLocalRate$, and (annual) changes to a country-specific commodity price index that uses as weights the share of the commodities exported by each emerging economy relative to total exports, deflated by the U.S. CPI, $\Delta RPcom$.[28] Thus, our framework examines the marginal information content of credit spreads, as proxied by EFI, conditional on the stance of external and domestic monetary policies as well as real shocks coming from commodity exports.[29]

We estimate the model using a Least Square Dummy Variable estimator (LSDV). The estimated coefficients are reported in Table 2.2. Numbers in parenthe-

[27] $USYield\,Curve$ = 10-year U.S. Treasury rate − 3-month U.S. Treasury rate

[28] $\Delta RPcom$ is computed by weighting the international prices of 44 distinct commodities in international markets by country-specific (constant) weights computed as each country's share in the country's total commodity exports. The source (and motivation) for using $\Delta RPcom$ comes from Fernández et al. (2015a) who argue that exogenous fluctuations in the price of commodities that emerging economies export are an important driver of their business cycles. See this work for further details on the construction of this variable.

[29] It may be argued that more variables could be added to model 2.3 in order to enhance the forecasting ability of our specification (e.g., industrial production). Such task, however, is not the aim of this investigation. Instead, our goal is to assess the information that the external financial indicator contains over and above a set of standard macro variables.

sis are t-statistics adjusted for standard errors clustered by country. The columns report results according to 5 alternative specifications that vary according to the set of controls used. In the first column, no controls are used. The second column reports results where we add the two global controls, $\Omega_t = [\Delta USYield\ Curve_t; \Delta RFF_t]$. The third and fourth specifications are reported in the next two columns where we sequentially include the two domestic controls without global controls, $\widetilde{\Omega}_t^k = [\Delta RLocalRate_{k,t}]$ and $\widetilde{\Omega}_t^k = [\Delta RPcom_{k,t}]$, respectively. The final specification reported in the last column reports results when all controls are included.

Our proxy for global financial conditions for emerging economies, ΔEFI, is a statistically significant predictor of economic activity in these countries. The coefficient associated with this variable is estimated to be negative and statistically significant at 5 percent significance level in all five specifications considered. Moreover, the magnitude of the estimated coefficient implies a strong and negative relationship between contemporaneous values of changes in EFI and future real output growth. According to the estimated coefficient from the last specification considered, $\widehat{\gamma} = -0.000022$, an increase in EFI of 100 basis points in the current quarter is correlated with a reduction of 0.22 percentage points in the output growth rate in the next quarter. This is a considerable reduction considering that such an increase is common in the data (e.g., a one standard deviation movement in ΔEFI is 195 basis points).

The two external controls, $\Delta USYield\ Curve_t$ and ΔRFF_t, are significant when added alone in Spec. 2 and when added jointly with the two country-specific controls in Spec. 5. Moreover, both have positive coefficients, which we interpret

Table 2.2: Panel Forecasting Regression

	Spec 1	*Spec 2*	*Spec 3*	*Spec 4*	*Spec 5*
ΔGDP_t	0.75***	0.82***	0.74***	0.69***	0.75***
	(28.32)	(22.59)	(28.70)	(14.34)	(21.42)
$\Delta\, EFI_t$	-0.000029**	-0.000027**	-0.000028**	-0.000025**	-0.000022**
	(-3.30)	(-3.35)	(-3.66)	(-2.72)	(-2.97)
$\Delta US\,Yield\,Curve_t$		0.0025*			0.0032**
		(2.27)			(2.66)
ΔRFF_t		0.0024**			0.0026**
		(2.70)			(2.67)
$\Delta R\,Local\,Rate_t$			0.00078		0.00046
			(1.43)		(0.86)
$\Delta R\,Pcom_t$				0.012	0.015*
				(1.38)	(2.44)
Adjusted R^2	0.681	0.704	0.686	0.688	0.718
Observations	371	371	371	371	371

Notes: This table presents the benchmark results of country fixed-effect panel regressions. The dependent variable is the one-quarter ahead annual real GDP growth rate at a quarterly frequency (ΔGDP_{t+1}). ΔEFI (measured in basis points) refers to annual changes in the external financial indicator. $\Delta US\,Yield$ (measured in percentage points) represents annual changes in the term spreads of 3-month and 10-year US treasuries. ΔRFF (measured in percentage points) is the annual change in the real Federal Funds rate, which is the effective nominal Federal Funds rate minus U.S. CPI inflation. $\Delta R\,Local\,Rate$ (measured in percentage points) is the annual change in the domestic real monetary policy rate (which is computed as the domestic nominal policy rate minus the domestic inflation rate). We use as a proxy for the policy rate the money market rate or the monetary-policy-related interest rate. $\Delta R\,Pcom$ refers to annual changes in the composite commodity index of Fernández et al. (2015a) (see Footnote 28 in the text for details on the construction of this index). The sample includes 7 emerging economies (Brazil, Chile, Korea, Malaysia, Mexico, Peru, Philippines) and the period of analysis is 1999.Q2-2013.Q2. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

as coming from the fact that monetary policy in the U.S. is countercyclical (i.e., interest rates increase to smooth stronger economic activity), which has positive spillovers for emerging economies. Neither of the country-specific controls is significant when added separately in Specs. 3 and 4. Only $\Delta RPcom_{k,t}$ is significant when estimated with all other controls in Spec. 5, in which case it has a positive coefficient, indicating that periods of high commodity prices are correlated with increases in macroeconomic activity.

2.5.2 Macroeconomic Effects of Shocks to the External Financial Indicator

We turn now to examining the dynamic macroeconomic consequences of shocks to EFI in the EMEs considered. We do so by running a simple bivariate panel structural vector autoregressive model (see Love and Zicchino, 2006 and Abrigo and Love, 2016) of output growth and changes in EFI. Formally, the SVAR model is

$$\mathbf{A}\mathbf{Y}_t = \mathbf{C} + \mathbf{B}_1\mathbf{Y}_{t-1} + ... + \mathbf{B}_p\mathbf{Y}_{t-p} + \Phi_t \tag{2.4}$$

where $\mathbf{Y}_t$ is a $2K$x1 vector that collects all pairs of real output growth (ΔGDP) and changes in EFI (ΔEFI) across the K emerging economies; $\mathbf{C}$ is a vector of constants with country fixed effects; Φ_t is a vector of $i.i.d.$ errors with mean zero and variance-covariance Θ, and matrix $\mathbf{A}$ captures the contemporaneous linkages across the variables, which we construct in a way that allows us to identify the shocks to ΔEFI. In particular, we assume that shocks to ΔEFI affect output growth only with a lag, while shocks to this variable may impact ΔEFI contemporaneously and also note that shocks to output may affect ΔEFI immediately. This identification strategy has been used by Gilchrist and Zakrajsek (2012) for the case of the United States, and in the context of EMEs by Uribe and Yue (2006).[30] This implies that the

[30]This identification strategy is rooted in the realistic assumption that financial variables (e.g., asset prices) react faster than real variables (e.g., production and investment decisions) due to various adjustment costs. Using this identifying assumption also allows our results to be compared more easily with previous studies.

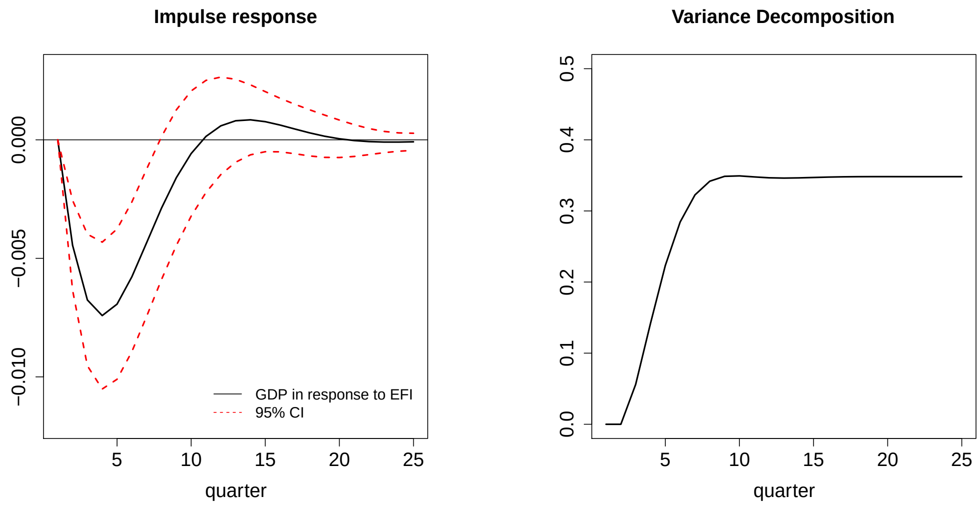
main diagonal of $\mathbf{A}$ is a sequence of 2x2 lower triangular matrices. Finally, we set the lag length p to one. A robustness section will later consider alternative timing identification assumptions as well as different lag specifications.[31]

The left panel in Figure 2.4 depicts the impulse response function of output growth to an orthogonalized shock in ΔEFI_t derived from the estimated panel SVAR. An unanticipated increase of one standard deviation in the orthogonal component of this variable, roughly 150 basis points, causes a protracted fall of output growth. Indeed, the macroeconomic consequences of this adverse financial shock are substantial: output growth falls as much as 0.75 percentage points one year after the shock when it reaches its trough. After that, growth gradually recovers and returns to its long-run mean six quarters ahead.

Another result that we derive from the estimated SVAR model is the forecast error variance decomposition (FEVD) for real output growth, depicted in the right panel of Figure 2.4. The share of the FEVD of output accounted by shocks to ΔEFI converges to 35 percent as the time horizon increases beyond one and a half years. This number is considerably higher than those from previous studies that quantified the role of risk premia shocks for emerging economies' business cycles that ranged between 12 and 15 percent (Uribe and Yue, 2006; Akinci, 2013). A key difference between these previous studies and ours is that they rely on measures of sovereign

[31] A potential concern emanating from the type of fixed effect panel VAR that we use here is the inconsistency of the least squares parameter estimates. Such bias, however, has been shown to decrease as the time dimension gets large (Judson and Owen, 1999), as in our empirical exercise. Still, we tested how robust our panel forecasting estimates are using the Anderson-Hsiao estimator. The results are reported in Table B.3 in Appendix B.2 and are qualitatively similar to those found in our benchmark case.

Figure 2.4: Panel VAR Impulse Response and Variance Decomposition of Real GDP Growth Rate



Notes: This figure presents the impulse response function and the forecast error variance decomposition of the bivariate panel VAR model. The left panel presents the impulse response function of annual real GDP growth rate to a 1 standard deviation shock in ΔEFI. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The right panel shows the forecast error decomposition of the real GDP growth rate associated with shocks to ΔEFI.

risk, unlike ours, which focuses on corporate risk.[32]

Summing up, the two methodologies employed so far, forecasting panel regressions and panel SVAR, have provided evidence that supports the hypotheses that spreads on bonds issued by *corporates* of EMEs in international capital markets have information on aggregate economic activity in these economies, and that exogenous perturbations to these spreads do have an impact on *future* economic activity. These results, we conjecture, are related to the considerable increase in foreign bond issuance by the private sector of EMEs, which we documented in the

[32]The SVAR in Uribe and Yue (2006) includes a larger vector of variables than the two that we analyze here (particularly investment, the trade balance and the foreign interest rate). Figure B.9 in Appendix B.2 presents the results when this larger model is run. They are quite similar to those found for the simpler bivariate VAR. The work by Akinci (2013) includes, in addition to the variables in Uribe and Yue (2006), the VIX. We will also examine this case in one of the extensions below.

previous section. We next consider extensions of our empirical explorations as well as various robustness tests.

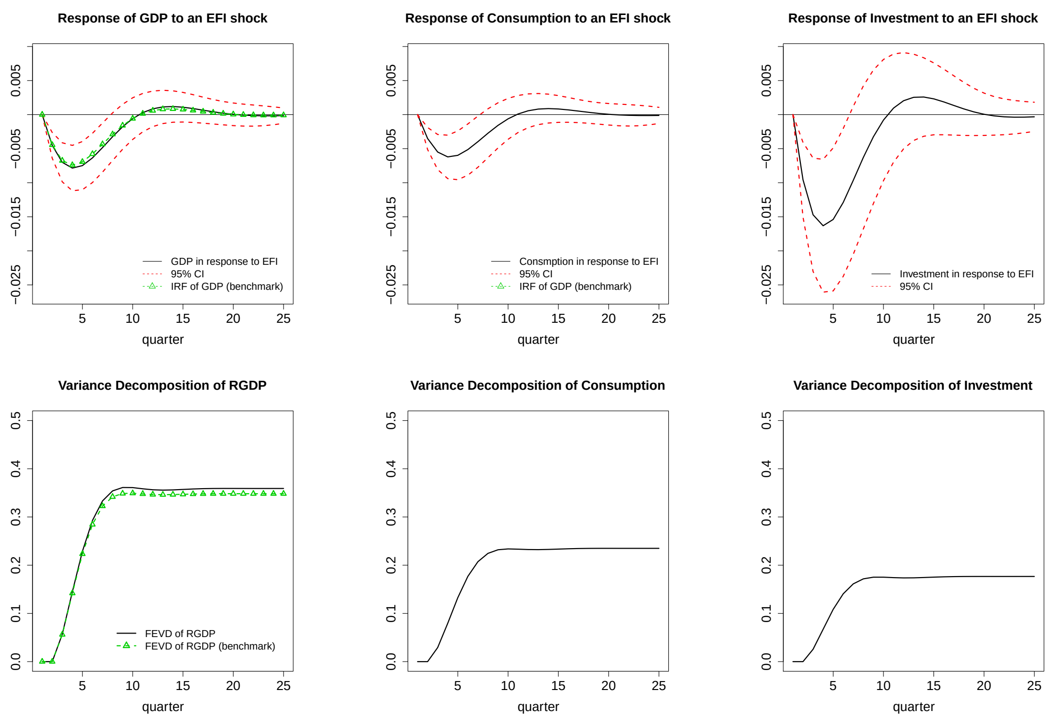
2.6 Extensions and Robustness Checks

2.6.1 Aggregate Consumption and Investment

As was described in Section 2, the literature has postulated two reasons why agents in EMEs may borrow funds from world capital markets. One is associated with factors that affect the level of aggregate investment while the other relates to forces that shape aggregate consumption. Hence the response of these two macroeconomic variables represent two channels, mutually non-exclusive, through which international financial shocks can affect aggregate economic activity in EMEs. In this section we extend our analysis by quantifying the degree of responsiveness of consumption and investment following shocks to ΔEFI. We do so by including these two variables in the SVAR characterized in equation (2.4) and deriving the impulse response functions in the expanded model. Our identification scheme remains the same in that we assume that shocks to ΔEFI affect real variables with a lag.

Results of this extension are reported in Figure 2.5. The upper panels of the figure display the impulse response functions for real growth in output, consumption and investment following a one S.D. shock in ΔEFI. The lower panels report the variance decomposition for each of these variables. There is evidence that both consumption and investment react to a positive shock to ΔEFI by falling below their average mean growth. In terms of the variance decomposition for consumption, 23 percent of consumption variance is accounted for by perturbation in EFI at medium-term horizons, above that of investment, which is 18 percent. Lastly, the share of variance in real output growth remains around 35 percent, as was found in the benchmark case.

Figure 2.5: Impulse Responses from Expanded Panel SVAR



Notes: This figure summarizes impulse response functions and forecast error variance decompositions of the expanded panel VAR model including $\{\Delta GDP_{i,t}, \Delta CONS_{i,t}, \Delta INV_{i,t}, \Delta EFI_{i,t}\}$. The top row presents an impulse response function of annual real GDP, consumption and investment growth rates to a 1 standard deviation shock to ΔEFI. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decompositions of real GDP, consumption and investment growth rates associated with shocks to ΔEFI. The green-triangle dotted lines represent bivariate panel VAR results from Figure 2.4. The Malaysian sample starts in 2005.Q1 due to data availability on investment.

2.6.2 Sovereign Risk

A potentially valid critique of our approach is that the real effects of external financial factors that we associate with corporate credit spreads in EMEs may be influenced by sovereign risk. As argued before, our focus on corporate risk in these economies comes from the stylized fact, presented in Section 2.3, that the large expansion of international bond issuance in EMEs since the early 2000s has mainly been concentrated in the corporate sector, not in the public sector. Still, it could be argued that the longstanding history of serial default by some EMEs may continue to make international investors wary of potential spillovers from sovereign risk to corporate risk. Such spillovers can arise if, for example, sovereign risk increases due to a rising public deficit, which then increases the probability that governments increase tax rates on the corporate sector or even expropriate private assets, raising their cost of borrowing in foreign markets.[33] Recently, Akinci (2013) found that shocks to the sovereign risk premia, proxied by JP Morgan's Emerging Markets Bond Index ($EMBI$), explained about 15 percent of business cycles in emerging economies, in line with earlier estimates from Uribe and Yue (2006) of about 12 percent.

To address this critique, in this subsection we assess how robust our benchmark

[33]This is just one of the many channels that may deliver a connection between sovereign and corporate risk. Another channel has been recently analyzed formally by D'Erasmo et al. (2013), where increases in sovereign risk constrain banks' ability to extend credit to firms because their balance sheet weakens as they hold sovereign bonds as part of their assets. Of course, the causality may go the other way around as well (i.e., from corporate to sovereign risk). The case of several crises in Asia in the 1990s (e.g., Korea) and the more recent experience in Ireland or Spain show how the deterioration of corporate balance sheets may turn into higher sovereign risk as the public sector absorbs much of the private illiquid debts. Our robustness check ought to be seen just as a crude first approximation to disentangling the links between corporate and sovereign risk.

results are when we include the country $\Delta EMBI$ in the forecasting panel regressions and panel SVARs. The results of the new panel regression are reported in the upper panel of Table 2.3, where we reproduce the same five specifications of Table 2.2. The results are virtually identical to the benchmark case. The coefficient associated with the change in EFI continues to be negative, large in absolute value, and statistically significant at 5 percent. The coefficient of $\Delta EMBI$ is positive but *not* significant at a 5 percent significance level in any of the five specifications considered. In an alternative specification when EFI is turned off (last column in Table 2.3, upper panel) and only $EMBI$ remains, its coefficient changes sign but continues not to be significant.[34]

The new panel SVAR that we run now includes $\Delta EMBI$ in addition to ΔGDP and ΔEFI. We assume that shocks to $EMBI$ can contemporaneously affect EFI but not vice versa. The impulse response of output growth from an identified one S.D. shock to ΔEFI in this expanded panel SVAR is reported in the top left panel of Figure 2.6. For the sake of comparison the figure also plots the response in the benchmark specification. The results continue to point to the same direction as those in the benchmark; an identified shock to ΔEFI generates a large and protracted fall in economic activity. Output growth falls as much as 0.6 percentage points three quarters after the shock when it reaches its trough. After that, growth gradually recovers and returns to its long-run mean approximately 8 quarters later. The dynamics track closely those in the benchmark impulse response. The bottom left

[34] We also take an alternative approach to control for sovereign risk using a principal component analysis. The coefficient associated with the change in EFI continues to be negative, large in absolute value, and statistically significant at 5 percent. See Appendix B.3 for details of the result.

Table 2.3: Panel Results Controlling for Sovereign Risk and Foreign Investors' Risk Aversion

	Spec 1	*Spec 2*	*Spec 3*	*Spec 4*	*Spec 5*	*w.o EFI*
Panel A. Controlling for sovereign risk						
ΔGDP_t	0.76***	0.83***	0.75***	0.66***	0.73***	0.72***
	(27.71)	(21.82)	(29.48)	(11.61)	(16.93)	(18.17)
$\Delta\, EFI_t$	-0.000035**	-0.000035***	-0.000034**	-0.000028**	-0.000027**	
	(-3.29)	(-4.36)	(-3.06)	(-3.08)	(-4.01)	
$\Delta EMBI_t$	0.000010	0.000012	0.0000094	0.0000097	0.000012	-0.000012
	(0.56)	(0.82)	(0.51)	(0.61)	(0.88)	(-1.31)
$\Delta US\,Yield\,Curve_t$		0.0023			0.0028*	0.0027*
		(1.78)			(2.17)	(2.04)
ΔRFF_t		0.0023*			0.0022*	0.0023*
		(2.20)			(2.34)	(2.18)
$\Delta R\,Local\,Rate_t$			0.00072		0.00040	0.00043
			(1.18)		(0.66)	(0.67)
$\Delta R\,Pcom_t$				0.019**	0.020***	0.024***
				(3.33)	(4.05)	(4.24)
Adjusted R^2	0.685	0.704	0.690	0.704	0.726	0.707
Observations	317	317	317	317	317	317
Panel B. Controlling for foreign investors' risk aversion						
ΔGDP_t	0.72***	0.79***	0.72***	0.66***	0.73***	0.72***
	(15.40)	(17.44)	(16.27)	(10.09)	(13.69)	(13.93)
$\Delta\, EFI_t$	-0.000019***	-0.000020***	-0.000019***	-0.000017***	-0.000018***	
	(-5.98)	(-8.94)	(-5.64)	(-5.29)	(-7.07)	
$\Delta EMBI_t$	0.0000099	0.000012*	0.0000094	0.0000096	0.000011	-0.0000014
	(1.22)	(2.07)	(1.03)	(1.11)	(1.67)	(-0.30)
ΔVIX_t	-0.00053**	-0.00050***	-0.00050**	-0.00042**	-0.00036**	-0.00049**
	(-3.83)	(-4.37)	(-3.66)	(-2.73)	(-2.70)	(-3.76)
$\Delta US\,Yield\,Curve_t$		0.0023			0.0027*	0.0026*
		(1.90)			(2.11)	(2.06)
ΔRFF_t		0.0021*			0.0021*	0.0021*
		(2.39)			(2.43)	(2.38)
$\Delta R\,Local\,Rate_t$			0.00048		0.00027	0.00024
			(0.84)		(0.45)	(0.38)
$\Delta R\,Pcom_t$				0.013**	0.015**	0.016**
				(2.75)	(3.50)	(3.92)
Adjusted R^2	0.709	0.725	0.710	0.717	0.735	0.729
Observations	317	317	317	317	317	317

Notes: This table shows results of country-fixed effect panel regression controlling for sovereign risk and foreign investors' risk aversion. Panel A reproduces the results of the five specifications in Table 2.2 adding $\Delta EMBI_t$ as an additional control variable for sovereign risk. Panel B reproduces the results in Table 2.2 adding both $\Delta EMBI_t$ and ΔVIX_t, the latter as a control for foreign investors' risk appetite. In both panels the last column drops the covariate for ΔEFI. In both panels the dependent variable is the annual real GDP growth rate at a quarterly frequency (ΔGDP_{t+1}). ΔEFI refers to annual changes in the external financial indicator. $\Delta USYield$ represents annual changes in the term spreads of 3-month and 10-year US treasuries. ΔRFF is the annual changes in the real Federal Funds rate, which is the effective nominal Federal Funds Rate minus U.S. CPI inflation. $\Delta R\,Local\,Rate$ is the annual changes in the domestic real monetary policy rate. $\Delta R\,Pcom$ refers to annual changes in the composite commodity index of Fernández et al. (2015a). The baseline sample includes 7 emerging economies (Brazil, Chile, Korea, Malaysia, Mexico, Peru, Philippines) and the period 1999.Q2-2013.Q2, but in these tables the 1999.Q2 observation for Chile and all observations for Korea are dropped because of lack of EMBI data. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at a 5 percent level, and *** indicates significance at 1 percent level.

panel in Figure 2.6 also presents the results in terms of FEVD for real output growth. The share of the FEVD of output accounted for by shocks to ΔEFI converges to 20 percent as the time horizon increases beyond one and a half years. This is close to half the share obtained in the benchmark case.[35]

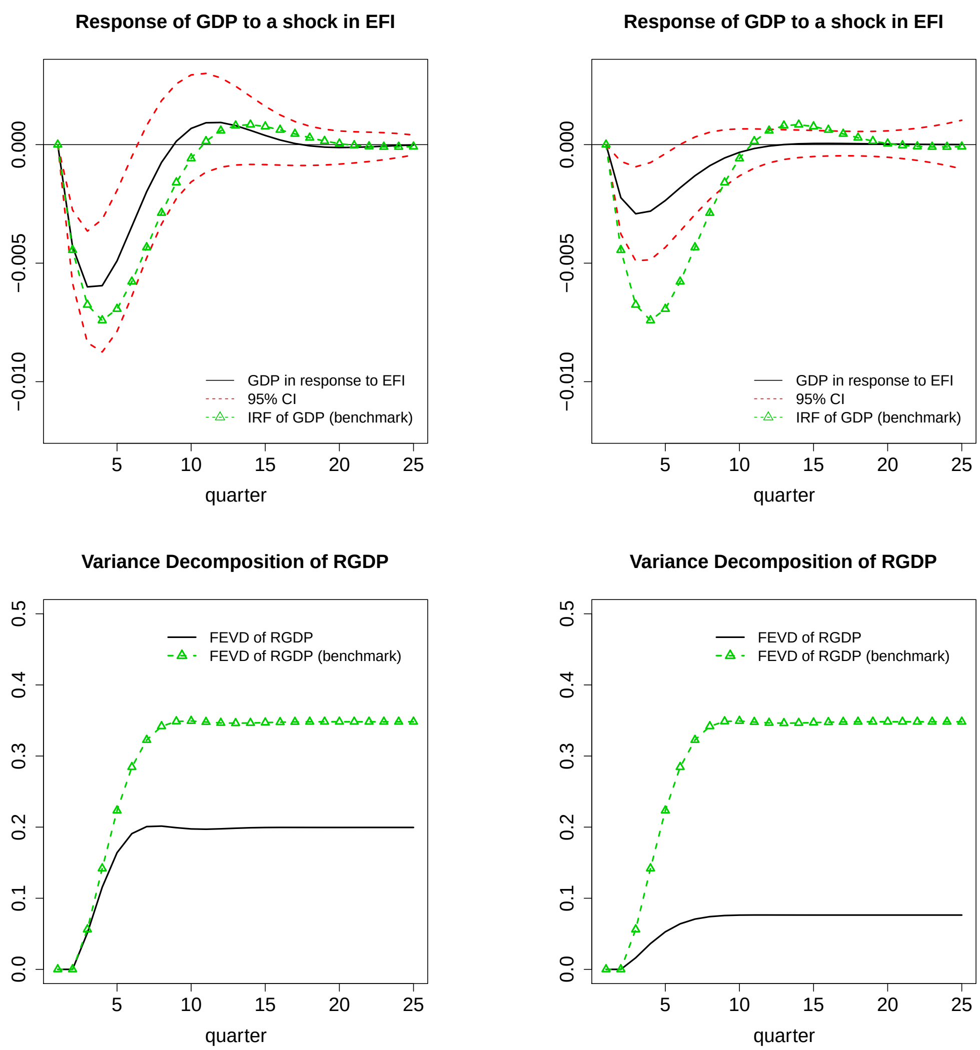
Overall, the results are robust to accounting for the possible role that sovereign risk may be playing in driving the dynamics of the external financial indicator. The macroeconomic effects are pervasive although marginally smaller. We interpret this as complementary evidence to that presented in previous studies that argue for a large role of sovereign risk when accounting for economic activity in emerging economies. Our results point to the relevance of shocks to the *corporate* risk premia as an *additional* source of fluctuations in real economic activity.

2.6.3 The VIX and Foreign Investors' Risk Aversion

In an influential work, Rey (2013) identified the VIX–a measure of uncertainty and risk aversion coming from the implied volatility of S&P 500 index options– as a variable that co-moves strongly with a global financial cycle in cross border capital flows. Moreover, Akinci (2013) finds that shocks to the VIX account for about 20 percent of movements in aggregate economic activity in a pool of emerging economies. Motivated by these works, in this section we explore to what extent movements in EFI are capturing changes in foreign investors' risk appetite that previous works have proxied by the VIX when quantifying the effects of these

[35] Appendix B.2 presents results when an alternative ordering is used such that shocks to EFI can affect $EMBI$ contemporaneously but not vice versa. For that case the results are even more similar to our benchmark results.

Figure 2.6: Impulse Response Controlling for Sovereign Risk and Foreign Investors' Risk Aversion



Notes: This figure summarizes impulse response functions and forecast error variance decompositions of the panel VAR models after controlling for sovereign and external risks. The first column shows results from a trivariate panel VAR model including $\{\Delta GDP_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables. The second column shows results from a trivariate panel VAR model including $\{\Delta GDP_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta VIX_t\}$ as an exogenous variable. The top row presents the impulse response function of annual real GDP growth to a 1 standard deviation shock to ΔEFI. Red dotted lines represent a 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents the forecast error decomposition of real GDP associated with shocks to ΔEFI. Green-triangle dotted lines represent results from Figure 2.4. Korea is excluded due to data availability on sovereign risk (EMBI). 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

changes in emerging economies. We address this question by including the VIX in the panel forecasting regressions and panel SVARs (already controlling for $EMBI$, as we do in the previous section).

The results of the new panel regression are reported in the lower panel of Table 2.3 where, again, we reproduce the same five specifications that we originally considered in Table 2.2. The coefficient associated with ΔEFI in Spec. 5, $\widehat{\gamma} = -0.000018$, falls relative to the benchmark (-0.000022) but remains statistically significant (at a 1 percent confidence level), as is the (negative) coefficient associated with the VIX.[36] In an additional experiment that we run, in the last column of that table, we remove EFI from the set of regressors. For that case, the coefficient associated with the VIX increases in absolute terms by nearly 40 percent.

The new panel SVAR that we run now includes ΔVIX_t as an exogenous variable in addition to ΔGDP, $\Delta EMBI$ and ΔEFI. The impulse response of output growth from an identified one S.D. shock to ΔEFI in this expanded panel SVAR is reported in the top right panel of Figure 2.6. Again, for the sake of comparison, the figure also plots the response in the benchmark specification. The results continue to point to the same direction as those in the benchmark: an identified shock to ΔEFI generates a fall in economic activity. Output growth falls but the magnitude of the fall is considerably reduced vis-à-vis the benchmark case. Output growth falls as much as 0.25 percentage points two quarters after the shock when it reaches its trough. Hence the trough is about 1/3 that of the benchmark specification.

The results of the variance decomposition for output growth go in the same

[36]The standard deviation of the change in the VIX is 10.3.

direction (bottom right panel in Figure 2.6). The share of the FEVD of output growth accounted by shocks to ΔEFI converges to about 8 percent, about a fourth of that in the benchmark case.

Overall, the results point to a crucial role of global risk appetite shifts in driving the macroeconomic effects of changes in EFI, which we view as complementary to Rey (2013) and Akinci (2013). This is mostly manifested in the dynamic responses of economic activity to shocks in this variable when controlling for endogenous responses to VIX fluctuations. Likewise, shocks to EFI, once VIX is taken into account, account for a much smaller variance share of output growth. Still, it is noteworthy that a non-trivial dynamic response of output growth continues to come from independent fluctuations in EFI. We view this as evidence that our external financial index does indeed capture external forces that affect economic activity in EMEs that are intrinsic to these economies, above and beyond global changes in investors' risk appetite.[37]

2.6.4 Alternative Filtering

Our benchmark results are computed using variables that are expressed in growth rates (or annual differences for spreads and interest rates). This is reasonable to the extent that growth rates are a simple and tractable measure of changes

[37] Table B.6 in Appendix B.2 contains further experiments where we include other observed external forces that may proxy for the global financial cycle, namely U.S. GDP growth. We find this variable not to have any explanatory value beyond that of the other controls. We also experimented by adding quarter-time fixed effects, which renders EFI no longer statistically and economically significant (although only for $h = 1$). We view this as additional evidence that EFI is capturing, although imperfectly, a financial common factor that is absorbed by the time fixed effect and materializes in a strong comovement across the EFIs.

in economic activity and foreign financial conditions. Yet, strictly speaking, first differencing is not a transformation that allows one to distinguish between trend and cyclical components of the variables considered, the latter being often the main object of analysis when thinking about changes in economic activity in the literature (see Introduction). We now assess the robustness of the benchmark results when variables are detrended in levels. For this purpose we use the Hodrick-Prescott filter, a commonly used detrending procedure in business cycle analysis.[38]

The upper panel of Table 2.4 reports the panel regression results with this alternative filter. All variables have been detrended using a smoothing parameter equal to $1,600$. The table reproduces the same columns reported in our benchmark case (Table 2.2). The results are both qualitatively and quantitatively robust. The estimated coefficient for EFI is now $\widehat{\gamma} = -0.000019$ for Specification 5, very close to the benchmark, and statistically significant at 10 percent. Figure B.12 in Appendix B.2 contains the impulse responses, which closely track those in the benchmark specification.

2.6.5 Alternative Forecasting Horizons

In our benchmark analysis we arbitrarily fixed the forecasting horizon to be one quarter, $h = 1$, in regression equation (2.3). We now extend our analysis by considering alternative forecasting horizons. In particular, we consider the cases of

[38] A potential shortcoming that this detrending measure poses is the fact that it is a two-sided filter and thus may display less accuracy when extracting the trend component in the end points of any time series. This may be particularly inconvenient in this case, given that our objective is to study the information content within a forecasting regression framework. We try to minimize this problem by using out-of-sample observations on the variables used for the period 2013.Q3-2014.Q4.

$h = 0, 2, 3, 4$. The case of $h = 0$ is one of "nowcasting" and can be thought as one where, because of reporting lags, economists typically do not observe current output growth, while financial asset prices that are used to construct EFI may be readily available.

The results of these alternative forecasting horizons are presented in the lower panel of Table 2.4. For comparison, the first column reports the results in our benchmark case where $h = 1$ and the other columns present, respectively, the cases of $h = 2, 3, 4$, and 0. In all cases, the specification presented is the one with all controls active (Spec. 5 from Table 2.2).

The coefficient associated with ΔEFI increases in size (and statistical significance) as h increases above 1, although not monotonically. The highest value, in absolute terms, is found for $h = 3$, in which case $\widehat{\gamma} = -0.000034$, a 55 percent increase relative to the one found in our benchmark case, and statistically, significant at 1 percent. The opposite occurs for the nowcast specification, where the coefficient reduces roughly to half of that in the benchmark specification, and is no longer significant at 10 percent. These results highlight the *forecasting* information content of EFI for economic activity in emerging economies. They are also in line with the serial correlations presented in Figure 2.3, which showed the strongest comovement between contemporaneous economic activity and lagged values of EFI in all the EMEs considered.[39]

[39] In terms of the controls, the U.S. yield curve loses its significance at longer lags, unlike the real Federal Fund rate ,which continues to be significant for $h \geq 1$, but not at $h = 0$. The coefficient on the Federal Funds rate also increases in magnitude until $h = 3$. The coefficient on the real local rate appears to be significant only at 10 percent when $h = 3$ and with a positive sign, which would signal that domestic monetary policy behaves in a countercyclical and forward-looking way. Finally, the coefficient on real commodity prices is strongest and statistically significant when $h = 0$

Table 2.4: Alternative Filtering Method and Forecasting Horizons

	Spec 1	*Spec 2*	*Spec 3*	*Spec 4*	*Spec 5*
Panel A. Alternative filter					
ΔGDP_t^c	0.74***	0.77***	0.73***	0.66***	0.70***
	(24.94)	(25.86)	(26.07)	(13.63)	(15.66)
EFI_t^c	-0.000027**	-0.000025**	-0.000026**	-0.000021*	-0.000019*
	(-2.93)	(-2.84)	(-3.11)	(-2.27)	(-2.29)
$US\,Yield\,Curve_t^c$		0.0010			0.0018*
		(1.23)			(1.99)
RFF_t^c		0.0019**			0.0022**
		(2.73)			(2.76)
$R\,Local\,Rate_t^c$			0.00048		0.000091
			(1.14)		(0.21)
$R\,Pcom_t^c$				0.015	0.017*
				(1.74)	(2.27)
Adjusted R^2	0.675	0.688	0.677	0.686	0.701
Observations	399	399	399	399	399
Panel B. Alternative forecasting horizon					
	h=1	*h=2*	*h=3*	*h=4*	*h=0*
ΔGDP_{t-1}					0.70***
					(13.39)
ΔGDP_t	0.75***	0.40***	0.063	-0.24**	
	(21.42)	(7.18)	(0.81)	(-2.68)	
$\Delta\,EFI_t$	-0.000022**	-0.000032***	-0.000034***	-0.000024**	-0.000013
	(-2.97)	(-3.88)	(-4.24)	(-2.74)	(-1.60)
$\Delta US\,Yield\,Curve_t$	0.0032**	0.0042*	0.0027	-0.00054	0.0011
	(2.66)	(2.41)	(1.48)	(-0.29)	(0.88)
ΔRFF_t	0.0026**	0.0048***	0.0057***	0.0046***	-0.00024
	(2.67)	(3.76)	(5.71)	(5.57)	(-0.41)
$\Delta R\,Local\,Rate_t$	0.00046	0.00100	0.00092*	0.00056	0.00041
	(0.86)	(1.54)	(2.19)	(0.95)	(0.79)
$\Delta R\,Pcom_t$	0.015*	0.020*	0.014	0.012	0.028**
	(2.44)	(2.29)	(1.66)	(1.29)	(3.46)
Adjusted R^2	0.718	0.449	0.360	0.328	0.721
Observations	371	371	371	371	371

Notes: This table shows two robustness checks. Panel A reproduces results in Table 2.2 using an alternative filter (Hodrick-Prescott filter with smoothing parameter $\lambda = 1600$; a superscript c represents the cyclical component of the filtered series). Panel B reproduces Spec. 5 in Table 2.2 for different forecasting horizons where the dependent variables are ΔGDP_{t+h} and h is a forecasting horizon. In Panel B, all variables are identically defined as in Table 2.2. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

2.6.6 Alternative Lag Order

In the benchmark SVAR characterized in equation (2.4) we arbitrarily set the number of lags to be one, $p = 1$. We now consider alternative lag specifications.[40] The upper left plot in Figure 2.7 reports the impulse responses of output growth for the alternative cases when $p = 2, 3$. For comparison, we also report the responses in the benchmark case. Solid lines represent impulses that are statistically significant at the 95 percent confidence level.

The results are qualitatively identical to the benchmark case. An orthogonal one S.D. shock to ΔEFI leads to a protracted fall in economic activity for all lag specifications considered. The trough also continues to lie one year after the shock. Quantitatively, the depth of the trough is 0.55 percent, slightly lower in magnitude than that in the benchmark case where the trough is around 0.75 percent.[41]

2.6.7 Alternative Identification Scheme

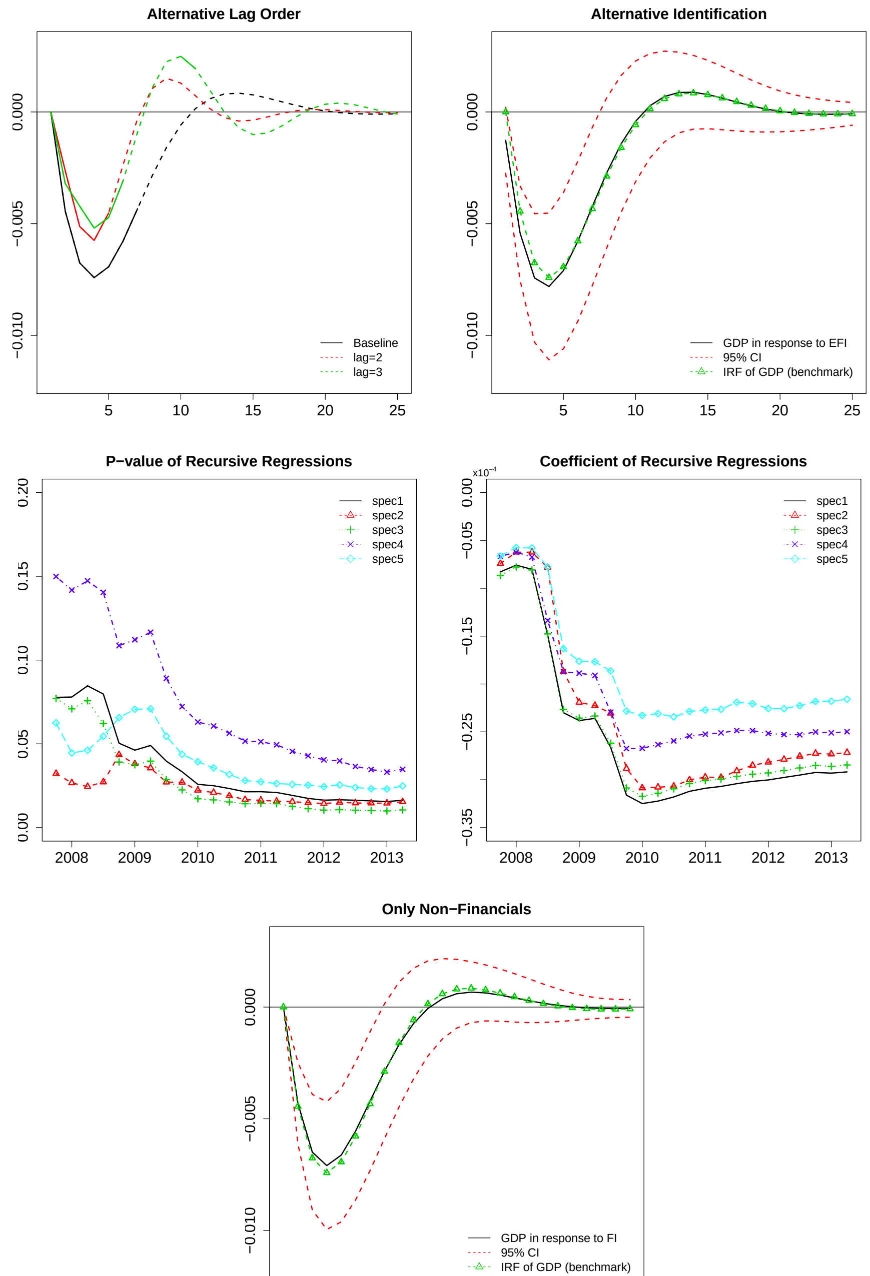
As argued before, the identification assumption used in the SVAR model—that shocks to ΔEFI affect output growth only with a lag while shocks to output may impact ΔEFI contemporaneously—has been common in the literature on both developed economies and EMEs. Nonetheless, we test the robustness of our results to an opposite timing/identification assumption where shocks to ΔEFI can affect

and then decreases in magnitude and statistical significance as the forecast horizon increases.

[40] Table B.5 in Appendix B.2 contains also extensions of the forecasting panel regression (2.3) with additional lags.

[41] Because the specification changes in these two alternatives, the size of the S.D. of the shock to ΔEFI also varies slightly. The shock has a magnitude of 147 and 142 basis points for the cases where $p = 2,3$, respectively.

Figure 2.7: Various Robustness Checks



Notes: This figure presents different robustness checks to our baseline results. The top left panel presents impulse response functions of annual real GDP growth rate to a 1 standard deviation shock to ΔEFI for two different lag order specifications ($p = 2$ and $p = 3$). Solid lines represent statistically significant responses at the 95% confidence level. The top right panel presents the impulse response function of the bivariate panel VAR with ΔEFI and ΔGDP with an alternative ordering in the Cholesky decomposition so that ΔEFI affects ΔGDP contemporaneously but not vice-versa. The middle left panel presents the p-value of the coefficients corresponding to ΔEFI from rolling panel regressions for the five specifications in Table 2.2 (starting in 1999.Q2 through 2007.Q4 and adding one quarter at a time). The middle right panel presents the estimated coefficients of ΔEFI from these rolling regressions. The lower panel presents the impulse response function of the benchmark bivariate panel VAR with ΔGDP and ΔEFI, where EFI is calculated after excluding bonds issued by financial firms.

output growth contemporaneously, but not vice-versa.

The results of this alternative identifying assumption are reported in the upper right plot of Figure 2.7. The plot reports the point estimates of the impulse response of output growth from a one S.D. shock to ΔEFI under the new identification scheme, along with its 95 percent confidence bands. For comparison, we also include the point estimate of the impulse responses in the benchmark case. The results are robust. On impact, there is a small drop in output growth of about 0.1 percentage point, although not statistically different from zero. The fall, however, continues until it bottoms after a year when output growth falls by 0.8 percentage points. The persistence of the shock on real economic activity is also similar, as output growth returns to its long-run mean around three years after the initial shock.

2.6.8 The Role of the World Financial Crisis and Subsequent Recovery

The stylized facts presented in Section 2.3 showed that, while the increasing trend of international debt securities started in the early 2000s, the trend accelerated most vigorously during the post-crisis recovery that began in mid-2009. Moreover, the time series of economic activity and EFI presented in Figure 2.3 show that the negative comovement between the two is most evident during the world financial crisis of 2008/9 and the subsequent recovery years. In this subsection we investigate how much the post-2008 period matters for our benchmark results. To do so we re-estimate regression equation (2.3) from the beginning of our sample, 1999.Q2, until 2007.Q4, three quarters prior to the collapse of Lehman Brothers. We then sequentially reestimate regression equation (2.3) by adding to the sample one more observation at a time while keeping the starting period fixed at 1999.Q2. For each case we document the estimated values and p-values of γ, the coefficient that links ΔEFI with future states of economic activity.

Results of this experiment are reported in the left and right middle panels of Figure 2.7. The left plot reports the recursive p-value statistics for each of the five specifications considered in Table 2.2. Four of the five coefficients considered are statistically significant in the first period considered up to 2007.Q4, and all five exhibit a decreasing trend in the p-values as new observations are added. Likewise, the right plot with the estimated γ coefficients for shows that as data of the crisis and the post-recovery are added, the negative coefficient increases in absolute terms.[42] We view this as indicating that the crisis and, more importantly, the post-recovery period account for most of the information content of EFI for future economic activity in emerging economies, although there is evidence that some of the predictive power predates the crisis. We posit that this result is a consequence of the large expansion in corporate bond issuance that began before the financial crisis, but accelerated afterwards, as documented in Section 2.3.

[42] The decrease in the p-values is, however, not monotonic for Specs. 2 and 5, which control for U.S. interest rates and monetary policy stance. In particular, the p-values increase between 2008.Q3 and 2009.Q3. One also observes that, for this period, the decrease in the estimated coefficients of γ slows down. This coincides with the most turbulent times of the financial crisis and the active use of monetary policy. The results seem to point that, for these two quarters, EFI's information content decreased in favor of the information already embedded in the U.S. interest rates.

2.6.9 Removing Financial Corporations' Bonds

We now assess the extent to which the high information content in EFI comes from bonds issued by non-financial corporates in EMEs. For that purpose we test whether our results hold if we remove from the construction of the EFI the bonds issued by financial corporations in each of the seven EMEs considered, using the methodology described in equations (2.1) and (2.2). This entails removing roughly half of the total number of bonds considered in the construction of the benchmark EFI.[43] With this modified EFI we re-run the panel SVAR model (2.4) and compare the new impulse responses of output growth to those from the benchmark case.

Results are reported in the lower plot in Figure 2.7. They are virtually identical to those coming from the benchmark case. There continues to be a large and protracted fall in economic activity following an orthogonal one S.D. shock to changes in the modified EFI. We view this as complementary to the evidence discussed in Section 2.3 that a considerable part of the rise in external bond issuance in emerging economies has been channeled via the corporate non-financial sector.

2.6.10 Excluding Countries

How much are the benchmark results driven by one of the EMEs considered? We assess this by redoing the panel forecasting regression equation (2.3) excluding each of the seven countries considered, one at a time.

[43] Among the total of 2,339 bonds considered in the benchmark case, 1,206 are bonds issued by banks or other financial institutions. Figure B.8 in Appendix B.2 plots the evolution in time of the size of the financial bonds that we remove for this experiment.

The results are presented in Table 2.5, which reports the coefficients from estimating Specification 5 in Table 2.2, sequentially excluding each of the seven EMEs considered one at a time. Qualitatively, the results are robust for each of the seven cases/columns considered. In all of them the estimated coefficient of γ continues to be statistically significant and of similar magnitude to the one estimated in our benchmark case. Our results are therefore not driven by an outlier country in the sample.[44]

2.7 Concluding Remarks

Access to world capital markets by the corporate sector may be viewed as a necessary condition for emerging economies to achieve sustainable long-run growth. But it can also entail the risk that changes in the financial conditions under which the private sector borrows in these markets may carry destabilizing consequences for real economic activity. These considerations are more pressing now than ever because the corporate sectors of many emerging markets have greatly increased their reliance on foreign debt.

Motivated by this observation, we have provided a comprehensive analysis that sheds light on the extent to which changes in the international financing conditions firms facing in the corporate sector in emerging economies are related to macroeconomic fluctuations. We do so first by providing a summary of the theoretical literature that postulates the channels through which such economic effects may oc-

[44]Figure B.13 and Table B.4 in Appendix B.2 also reports the results for cases where the SVAR and forecasting regressions are estimated for each country independently.

Table 2.5: Panel Regression Results Excluding Countries One at a Time

	w.o Brazil	*w.o Chile*	*w.o Korea*	*w.o Mexico*	*w.o Malaysia*	*w.o Peru*	*w.o Philippines*
ΔGDP_t	0.74***	0.76***	0.73***	0.76***	0.76***	0.72***	0.76***
	(17.34)	(24.05)	(17.11)	(23.31)	(21.14)	(16.02)	(21.41)
$\Delta\, EFI_t$	-0.000033***	-0.000022**	-0.000020**	-0.000020**	-0.000020**	-0.000021*	-0.000020**
	(-4.69)	(-2.92)	(-2.81)	(-2.87)	(-2.88)	(-2.20)	(-2.91)
$\Delta USYieldCurve_t$	0.0024	0.0038**	0.0028*	0.0034**	0.0030*	0.0029	0.0040**
	(1.92)	(3.05)	(2.07)	(2.67)	(2.21)	(1.87)	(3.63)
ΔRFF_t	0.0017**	0.0027*	0.0022*	0.0027*	0.0024*	0.0029*	0.0031**
	(2.59)	(2.38)	(2.23)	(2.37)	(2.30)	(2.54)	(3.34)
$\Delta R\, Local\, Rate_t$	0.00068	0.00067	0.00043	0.00048	0.000095	0.00021	0.00066
	(1.10)	(1.12)	(0.74)	(0.78)	(0.23)	(0.40)	(0.91)
$\Delta R\, Pcom_t$	0.0098	0.014	0.020**	0.013*	0.014*	0.017*	0.018**
	(1.80)	(1.92)	(3.63)	(2.10)	(2.08)	(2.23)	(2.80)
Adjusted R^2	0.734	0.721	0.724	0.694	0.725	0.713	0.728
Observations	318	318	318	318	318	318	318

Notes: This table reproduces Spec (5) in Table 2.2 dropping one country at a time from the pool of EMEs considered in the benchmark estimation (the dropped country is reported in the top of each column). All variables are identically defined as in Table 2.2. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

cur. We then provide empirical evidence of recent increases in international credit access using information for a pool of 17 emerging economies. In particular, we document increases in corporate bond issuance denominated in USD. We relied on this stylized fact to construct an indicator of external financial conditions for several of these economies using option-adjusted spreads from bonds issued in foreign capital markets by the corporate sector that are traded in secondary markets. We show that changes in this indicator are strongly correlated with future economic activity in EMEs and that identified shocks to the indicator entail large and protracted falls in economic activity.

While we have been silent about the policy implications of our analysis, the results we have presented do warrant a more normative analysis of the extent to which policy actions can (or should try to) mitigate the effects that changes in foreign financing conditions of the corporate sector may have on economic activity in EMEs. The large increase in the stock of foreign debt in the balance sheet of EMEs' corporates will certainly keep this question at the forefront of international macroeconomics for the years to come. Hopefully the results in this paper will motivate further work to shed light on this question.

Appendix A: Appendix for Chapter 1

A.1 TFP Estimation

In this section of the appendix, I provide details of how variables used in the TFP estimation are constructed. I heavily follow Covas and Den Haan (2011) and Imrohoroglu and Tüzel (2014) in cleaning data and defining variables. All balance sheet variables are from Compustat. Capital letters in parentheses represent Compustat mnemonics. Financial and utility firms (SIC 4900-4949 and 6000-6999, NAICS 22 and 52-53) are deleted from the sample, which is a standard procedure in the literature. I further drop postal service, courier and messengers, and the warehousing and storage industry (NAICS 49), since less than 250 observations are available for the entire sample period. Firms belonging to an unclassified industry (NAICS 99) are dropped from the sample.

Firm-year observations with non-positive total assets (AT), total sales (SALE), operating income before depreciation and amortization (OIBDP), number of employees(EMP), gross property, plant, and equipment (PPEGT), or net property, plant, and equipment (PPENT) are dropped from the sample. These variables are necessary inputs to construct variables used in the TFP regression.

To ensure data reliability, firm-year observations violating the accounting identity (total assets equals total liabilites plus stockholders' equity) by more than 10% are dropped from the sample.

Observations with a fiscal year ending between April and August are dropped from the sample in order to minimize calendar and fiscal year mismatch.

Value-added ($VA_{i,j,t}$)is defined as total sales (SALE) net of materials. Materials are defined as total expenses minus labor expenses. Total expenses are measured as total sales (SALE) minus operating income before depreciation and amortization (OIBDP), and labor expenses are defined as the number of employees (EMP) times the industry-level average annual wage. I mostly use 2-digit NAICS-level industry wages. I use 3- or 4-digit industry level wages if available. The source of the average annual wage data is the Bureau of Labor Statistics [link]. I mostly use a 2-digit NAICS level value-added price deflator to calculate real values of value-added. However I use 3- or 4-digit industry level if available. The source of the value-added price deflators is the Bureau of Economic Analysis. The number of employees, $L_{i,j,t}$ is directly available from Compustat (EMP).

I define the stock of capital $K_{i,j,t}$ as lagged net property, plant, and equipment (PPENT). However, measuring the real capital stock is not straightforward since investments are made at different points of time. To address this issue, I calculate an average age of capital, and deflate the capital stock accordingly using an aggregate non-residential fixed investment deflator from the Bureau of Economic Analysis, which can easily be downloaded from Federal Reserve Economic Data.[1] For example,

[1]Although Bureau of Labor Statics provides [link] an investment good deflator at 2- and 3-digit NAICS level, the series starts only in 1990. Since the stock of capital is built by a sequence of investment over time, it is necessary to know the price deflator of investment goods purchased prior to 1990, unless all investments are made after 1990. For the reason, using an industry level

if a firm's average age of capital in 2000 is 3 years, I deflate net property, plant, and equipment (PPENT) using its deflator in 1997. Average age of capital is defined as a 3-year moving average of accumulated depreciation (DPACT) divided by current depreciation (DP).

Intermediate inputs are defined as materials, which are defined above. I mostly use 2-digit NAICS level industry intermediate input price deflators. However I use 3- or 4-digit industry level data if available. The source of data is the Bureau of Labor Statistics.

The TFP estimation yields a total of 68,964 firm-year TFP observations for 8,500 unique firms (which is approximately 85% of the sample included in the main regression.) Note that this is *not* identical to the number of firm-year observations and unique firms which are used to estimate equation (1.16). There are fewer observations available for the variables required for the TFP regression than for the main regression. I do not necessarily require observations included in the main regression to be included in the TFP regression. This procedure maximizes the number of observations for the main regression.

A.2 Variable Definition

On variable definitions and firms included in the main regression sample, I mostly follow Covas and Den Haan (2011). Capital letters in parenthesis represent Compustat mnemonics. Financial and utility firms (SIC 4900-4949 and 6000-6999, NAICS 22 and 52-53) are deleted from the sample, which is a standard procedure

deflator of investment causes a substantial loss of observations.

in the literature. I further drop postal service, courier and messengers, and warehousing and storage (NAICS 49), since less than 250 observations are available for the entire sample period. Firms belonging to an unclassified industry (NAICS 99) are dropped from the sample.

Firm-year observations with negative total liabilities (LT), long-term debt (DLTT), debt in current liabilities (DLC), stock price (PRCC_F), liquidating value of preferred stock (PSTKL), dividends to preferred stock (DVP), sales of common and preferred stocks (SSTK), and purchases of common and preferred stocks (PRSTKC) are dropped from the sample. Firm-year observations with non-positive stockholders' equity (SEQ) are dropped from the sample.

If firms are involved in major mergers (Compustat footnote code AB), they are excluded from the sample. GM, GE, Ford, and Chrysler are dropped from the sample since they are substantially affected by accounting changes in 1988. If a firm-year observation violates the accounting identity (total assets (AT) equals total liabilites (LT) plus stockholders' equity(SEQ)) by more than 10%, it is dropped from the sample. Firm-year observations with stockholders' equity (SEQ)-to-total asset (AT) ratio below 0.01 or total debt-to-total asset (AT) ratio greater than 1 are dropped from the sample. Total debt is defined as the sum of debt in current liabilities (DLC) and long-term debt (DLTT). This restriction is to exclude firms which are virtually bankrupt, or in substantial financial distress. Lastly, observations with a fiscal year ending in between April and August are dropped from the sample in order to minimize calendar and fiscal year mismatch.

The definitions of firm level balance sheet variables are as follows (Items in double quotation marks refer to variable names in the Compustat manual. All variables are deflated by the U.S. CPI):

- $Equity\,finance_t$: "**Sale of Common and Preferred Stock (SSTK)**" minus "**Purchase of Common and Preferred Stock (PRSTKC)**" divided by lagged "**Assets - Total (AT)**"

- $Debt\,finance_{i,t}$: Changes in total debt divided by lagged "**Assets - Total (AT)**" where total debt is "**Debt in Current Liabilities - Total (DLC)**" plus "**Long-Term Debt - Total (DLTT)**"

- $Leverage_{i,t}$: Total debt divided by lagged "**Assets - Total (AT)**" where total debt is "**Debt in Current Liabilities - Total (DLC)**" plus "**Long-Term Debt - Total (DLTT)**"

- $Cashflow_{i,t}$: "**Income Before Extraordinary Items (IB)**" minus "**Depreciation and Amortization (DP)**" divided by lagged "**Assets - Total (AT)**"

- $Tobin's\,Q_{i,t}$: "**Common Shares Outstanding (CSHO)**" times "**Price Close - Annual - Fiscal (PRCC_F)**" plus "**Preferred Stock - Liquidating Value (PSTKL)**" plus "**Dividends - Preferred/Preference(DVP)**" plus "**Liabilities - Total (LT)**" divided by lagged "**Assets - Total (AT)**"

- $Sales\,growth\,rate_{i,t}$: "**Sales/Turnover (Net) (SALE)**" minus lagged "**Sales/Turnover (Net)**" divided by lagged "**Assets - Total (AT)**"

- $Asset\,growth\,rate_{i,t}$: "**Assets - Total (AT)**" minus lagged "**Assets - Total (AT)**" divided by lagged "**Assets - Total (AT)**"

- $firm\,size_{i,t}$: log of lagged "**Assets - Total (AT)**"

Appendix B: Appendix for Chapter 2

B.1 Data Sources and Definitions

B.1.1 Description of Bonds from Dealogic's DCM Database and Definition of International and Domestic Debt Securities

The bond issuance data used in this paper are sourced from Dealogic DCM database. The figures show country aggregations of transaction-level data. The database includes a total of 625,074 bond tranches (479,678 unique bond deals). The totals shown in Figures B.2-B.5 and B.6-B.7 of the Appendix are aggregations for all non-government bonds for the 17 countries in the sample (a total of 13,287 bond tranches). The figures include issuance of government-owned companies (such as utilities, oil companies, universities, and transport systems).

The definition of an international debt security (IDS) used in the paper follows the new methodology implemented by the Bank for International Settlements to define international debt securities. This methodology compares the location where the bond is issued with the residence of the issuer. Following the BIS' practice, the place of residence of a firm is considered to be the jurisdiction where it is incorporated. To identify the place where the bond is issued we use information on the country where the security (or securities as a bond may be composed of multiple individual securities) is listed, the ISIN number (or numbers) assigned to the security (or securities), and the governing law.

A bond is classified as an IDS if it is listed in multiple countries, or if it is listed with an international central depository, or if it includes securities that have been issued ISIN numbers in multiple countries. A security is also considered an IDS if the residence of the issuer is different from the country where the security is issued an ISIN, or if it is different from the security's governing law. Bonds with incomplete information on listing place, ISIN number, and governing laws are classified as international securities if the data provider classifies the bond as foreign by market type.

Similar rules are applied to classify a security as domestic for cases in which the residence of the issuer is the same as the governing law, or the same as the ISIN nationality, or the same as the listing place, or all three conditions apply at once (and given no contradiction with classification as international security, and a unique listing place and/or unique ISIN nationality). Given lack of information on ISIN number, listing place, and governing law, the bond is classified as domestic if the vendor designated by Dealogic is domestic by market type.

Applying these rules, we are able to correctly classify all bonds in our sample of 17 EMs.

B.1.2 OAS data

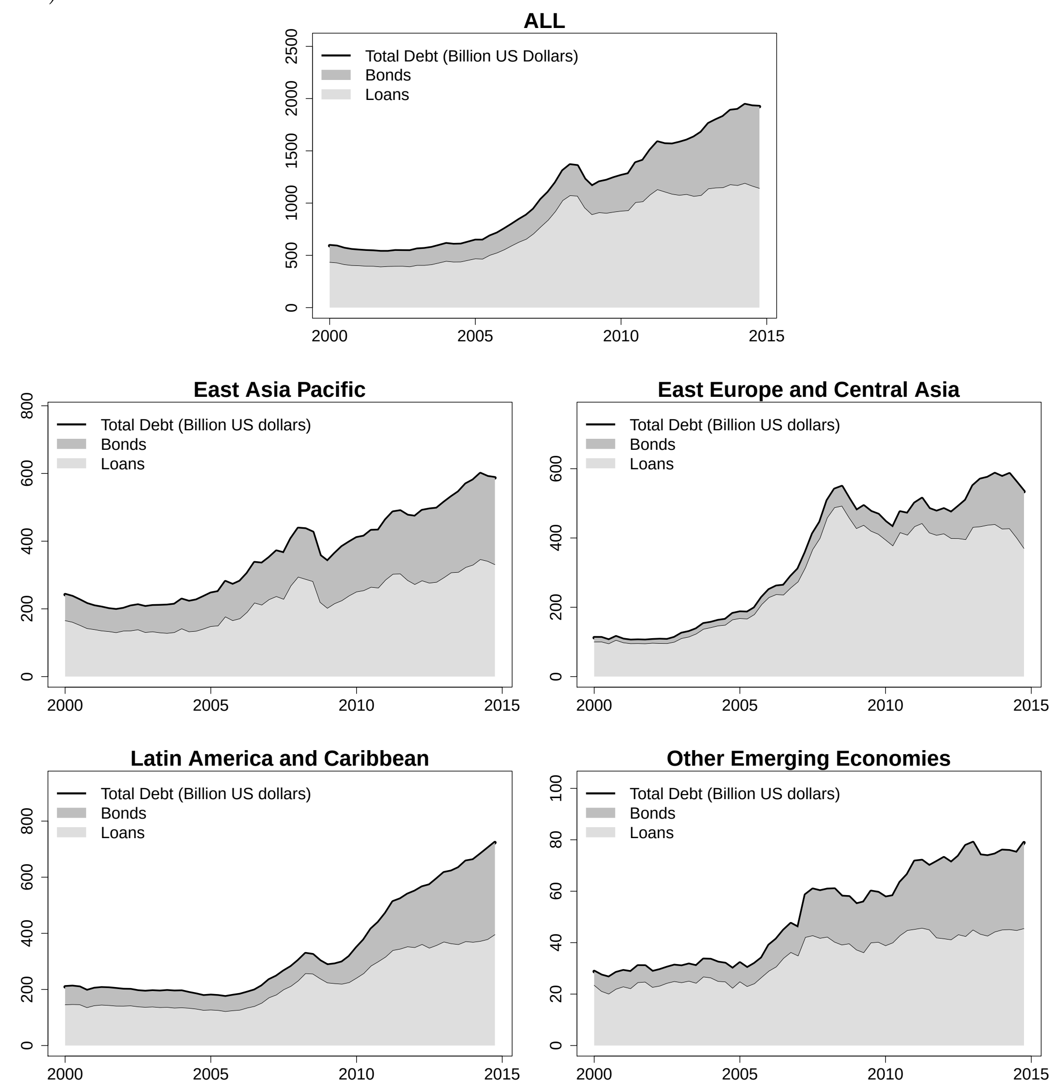
We use data on option-adjusted spreads from Bloomberg. We specifically used the mnemonic `OAS_SPREAD_BID` to retrieve quarterly spreads for all corporate bonds with available OAS data in Bloomberg for the seven countries in our sample. The Bloomberg tickers of the bonds in our sample are available upon request.

B.1.3 Other data

We use data on outstanding stocks of international and domestic debt securities from the BIS' Securities Database. We also employ data on cross-border loans from the BIS' Locational Banking Statistics database. For GDP data we collected data from the IMF's International Financial Statistics database. We also used data on sovereign debt held by private banks for five Latin American countries, sourced from the Inter-American Development Bank (IDB) LAC Debt Group database. Data used in the panel regressions and SVAR models are from Fernández et al. (2015a) (domestic GDP, consumption and investment; U.S. yields, interest rates, and GDP growth; and commodity prices; see that paper for more details).

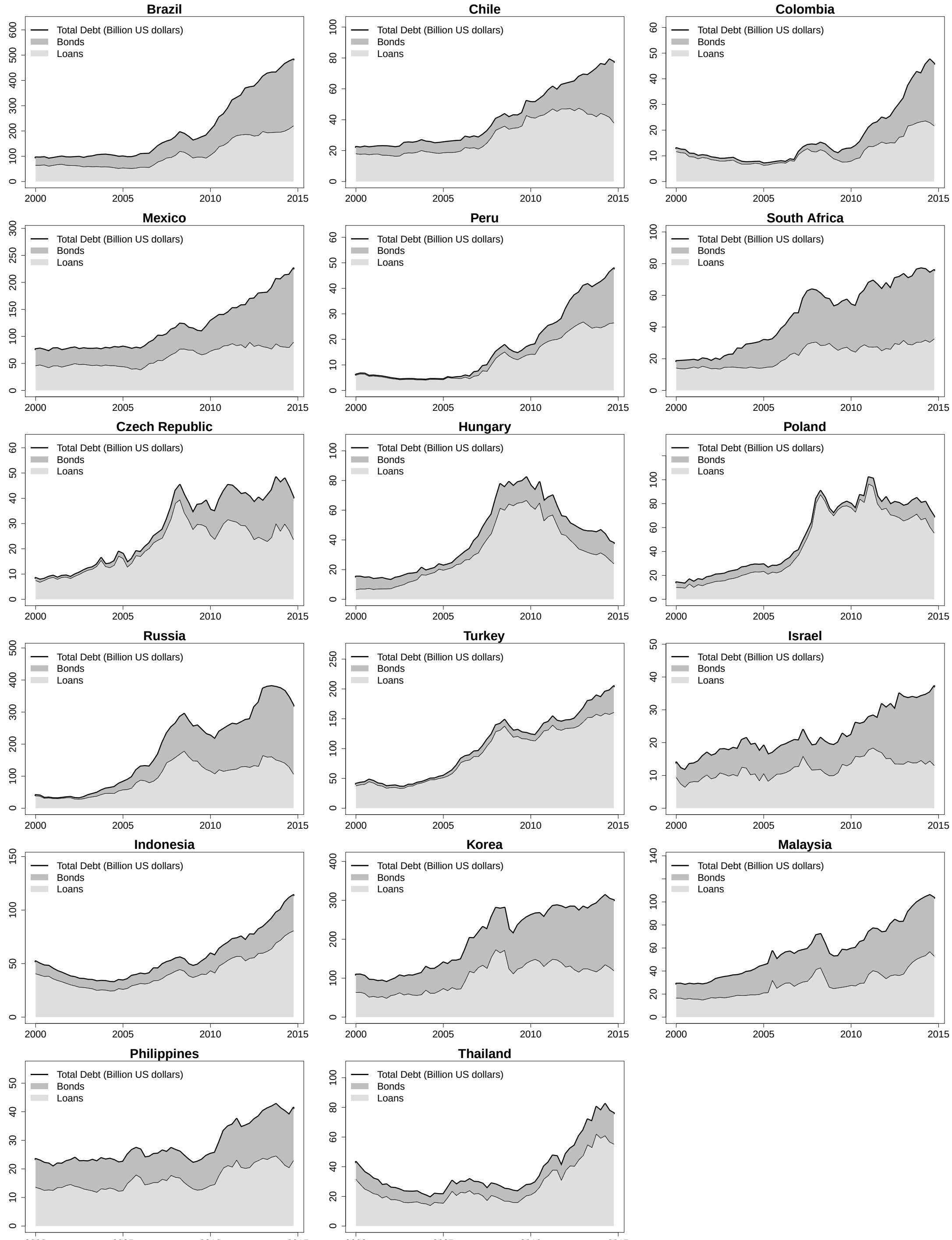
B.2 Additional Figures and Tables

Figure B.1: Stock of Private Sector International Debt in EMEs (on a Residence Basis)



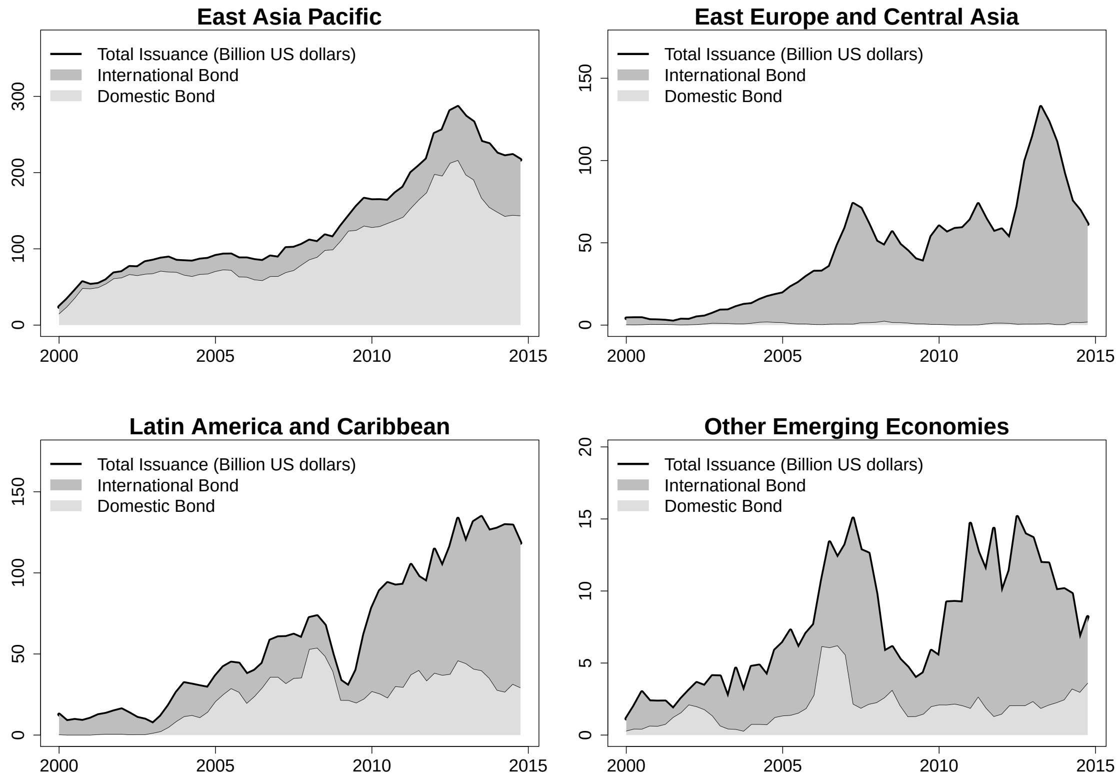
This figure is a replication of Figure 2.1 measuring the stock of securities on a residence basis, rather than on a nationality basis. As in Figure 2.1, the figure shows the aggregate stock of private sector international debt for 17 emerging economies, decomposing the outstanding stock into cross-border bank loans and international debt securities. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

Figure B.2: Stock of Private Sector International Debt in EMEs by Country



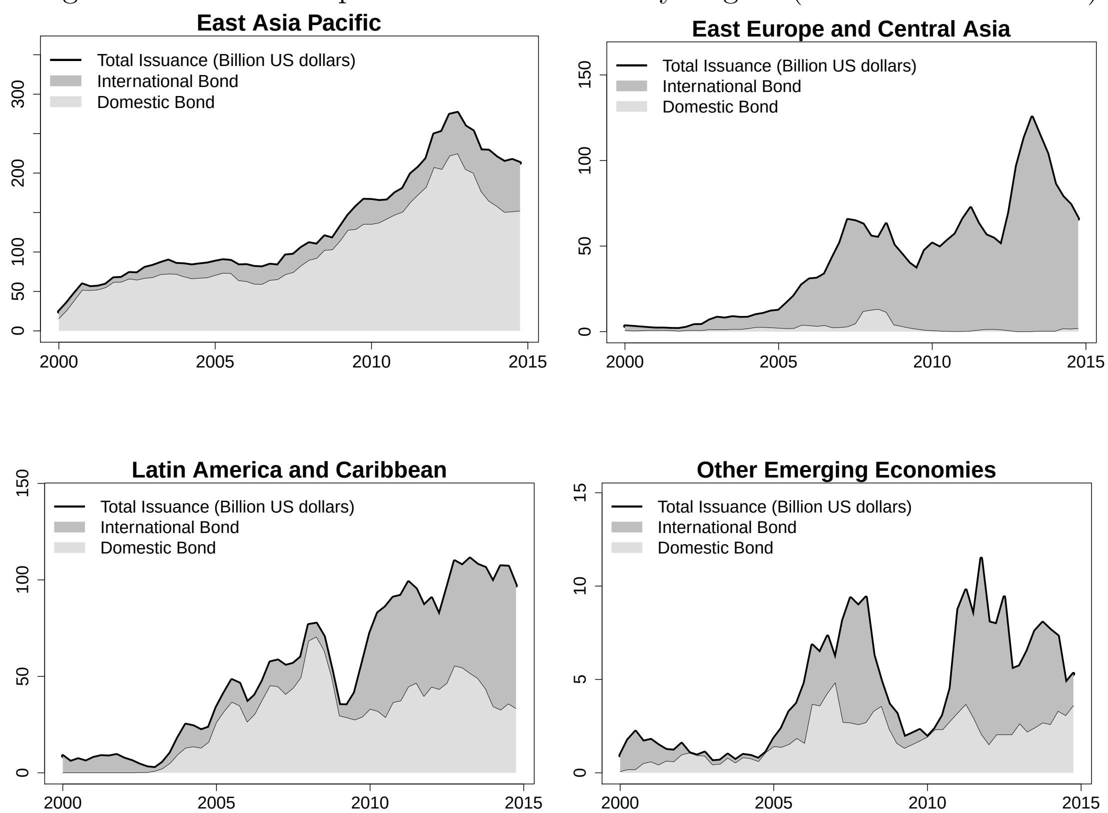
Notes: This figure presents country dissaggregations of the stocks of international debt shown by region in Figure 2.1. As in Figure 2.1, this figure shows the aggregate stock of private sector international debt for 17 emerging economies, decomposing the outstanding stock into cross-border bank loans and international debt securities. The stock of securities is on a nationality basis. The private sector includes all financial institutions and non-financial corporations. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from the BIS Locational Banking Statistics and BIS Securities Statistics databases.

Figure B.3: Corporate Gross Bond Issuance in EMEs by Region



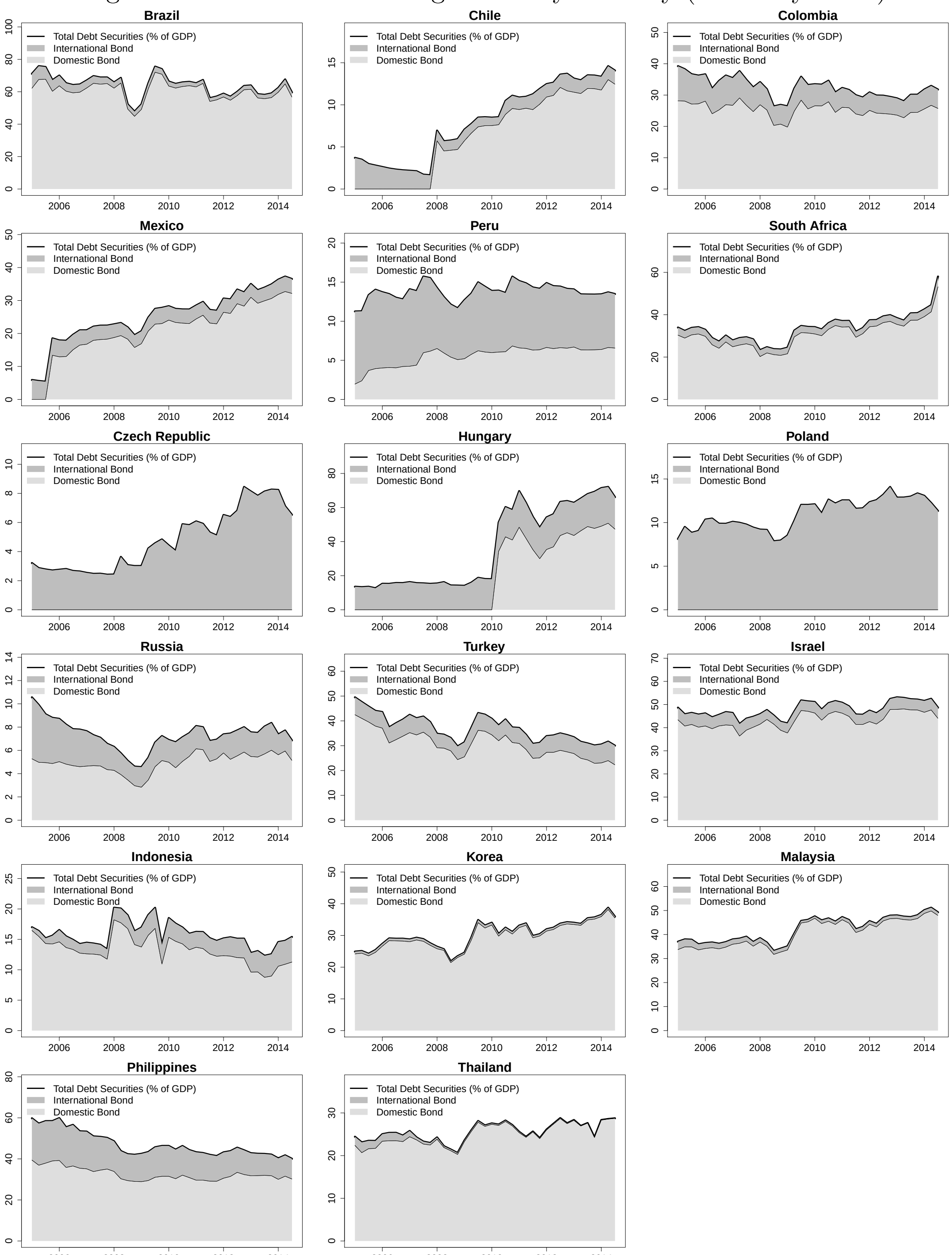
Notes: This figure presents regional aggregates of country-by-country gross issuance shown in Figure 2.2. As in Figure 2.2, this figure shows gross issuance of international and domestic debt securities based on a nationality basis. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See Appendix B.1 for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

Figure B.4: Gross Corporate Bond Issuance by Region (on a Residence Basis)



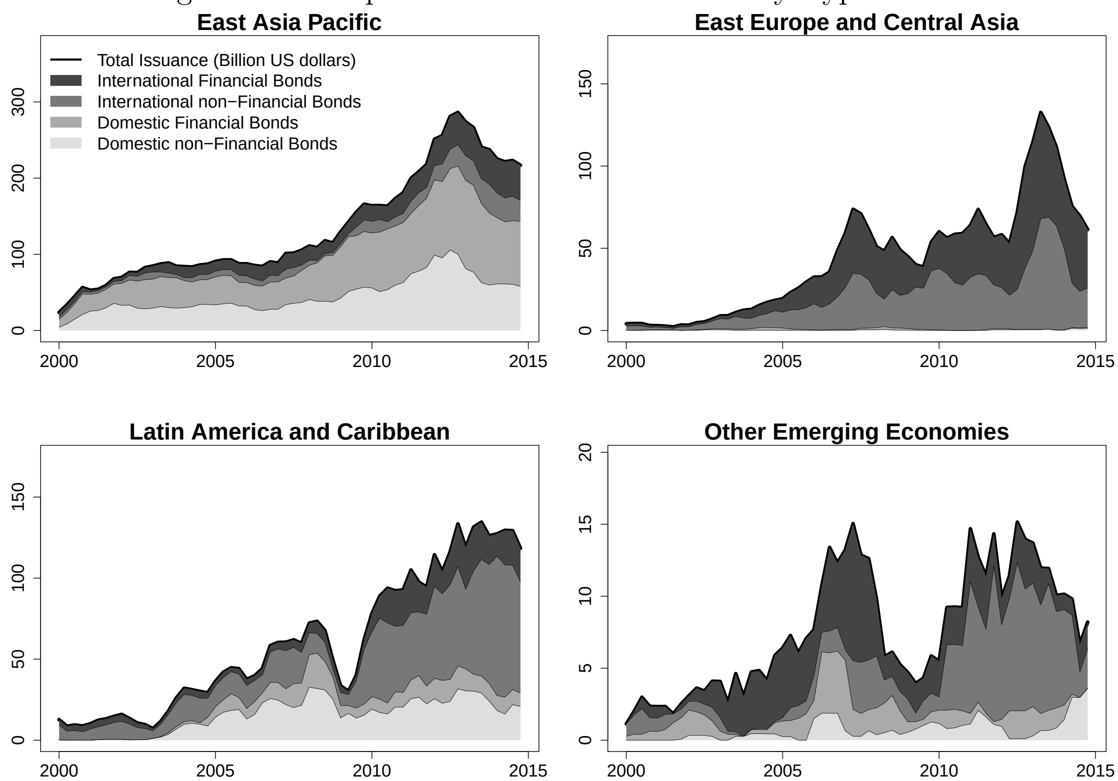
Notes: This figure reproduces regional aggregates of gross issuance shown in Figure B.3, but on a residence basis. As in Figure B.3, the regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See Appendix B.1 for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

Figure B.5: Stocks of Sovereign Debt by Country (scaled by GDP)



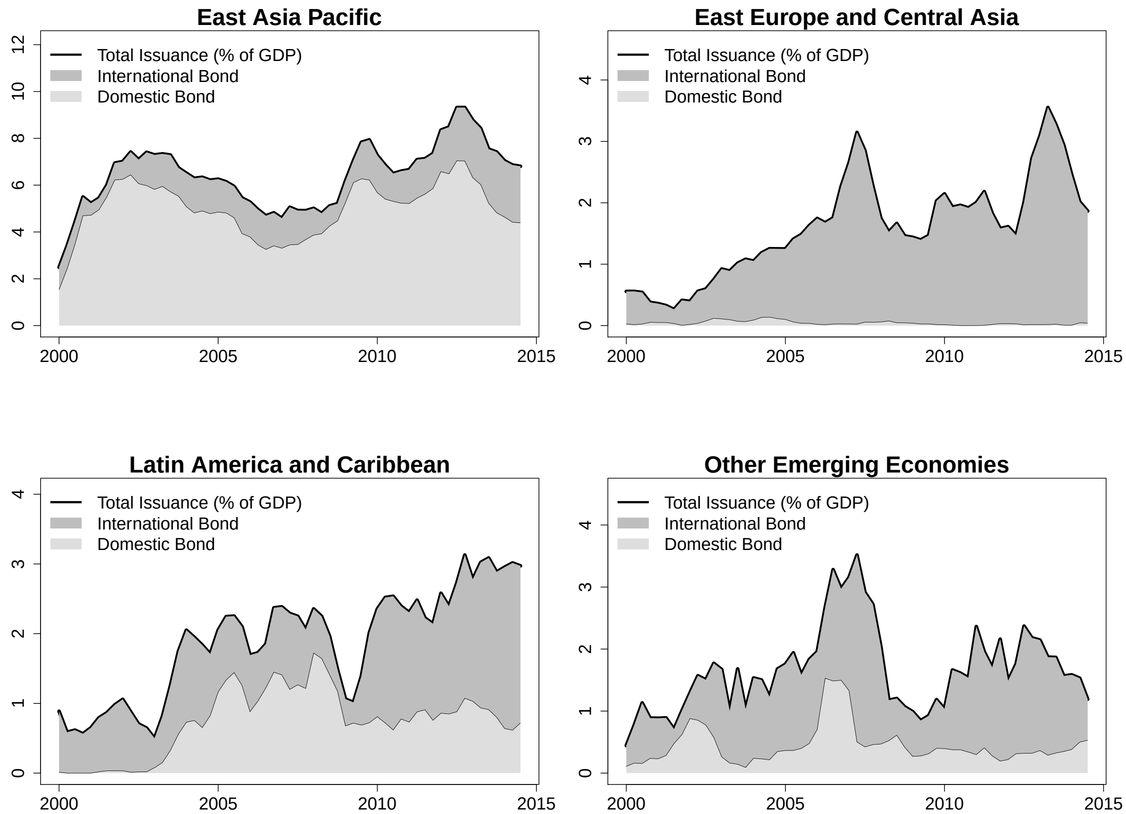
Notes: This figure shows the aggregate stock of sovereign debt in 17 emerging economies, decomposing the outstanding stock into international and domestic debt securities. The quarterly stocks are scaled by annual GDP (i.e., the sum of last 4 quarters). Data on stocks are from the BIS Securities Statistics database and data on GDP are from the IMF International Financial Statistics Database.

Figure B.6: Corporate Gross Bond Issuance by Type of Issuer



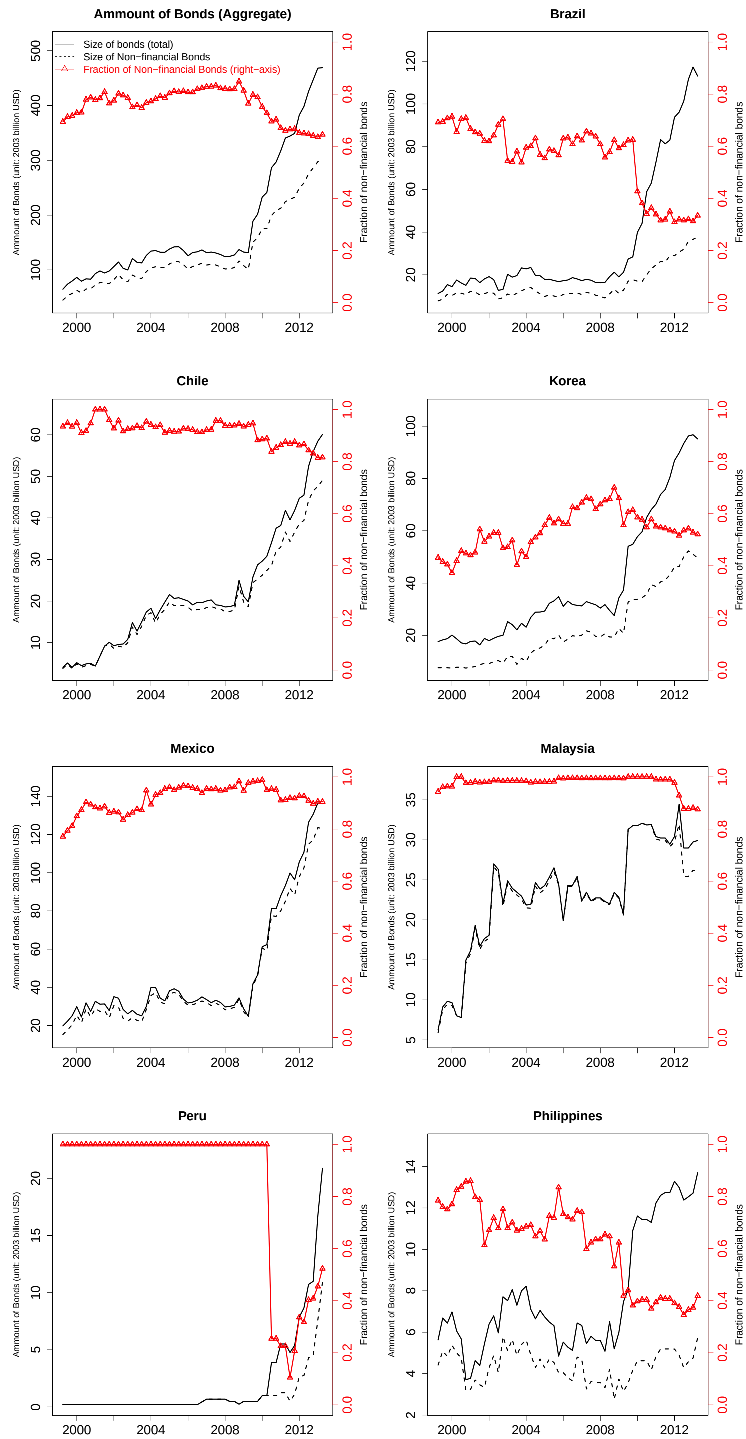
Notes: This figure shows gross issuance of international and domestic debt securities by region based on a nationality basis, as in Figure B.3, further decomposing issuance by issuer into non-financial and financial corporations. Financial corporations include issuance by any firm classified by the data vendor as operating in the "Finance" and "Insurance" sectors, and issuance by Closed End funds and Holding Companies. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel. The data are presented in billions of current U.S. dollars and sourced from Dealogic's DCM database. See Appendix B.1 for a description of how country aggregates are obtained from transaction-level data and for a definition of international and domestic debt securities.

Figure B.7: Corporate Gross Bond Issuance by Region (Scaled by GDP)



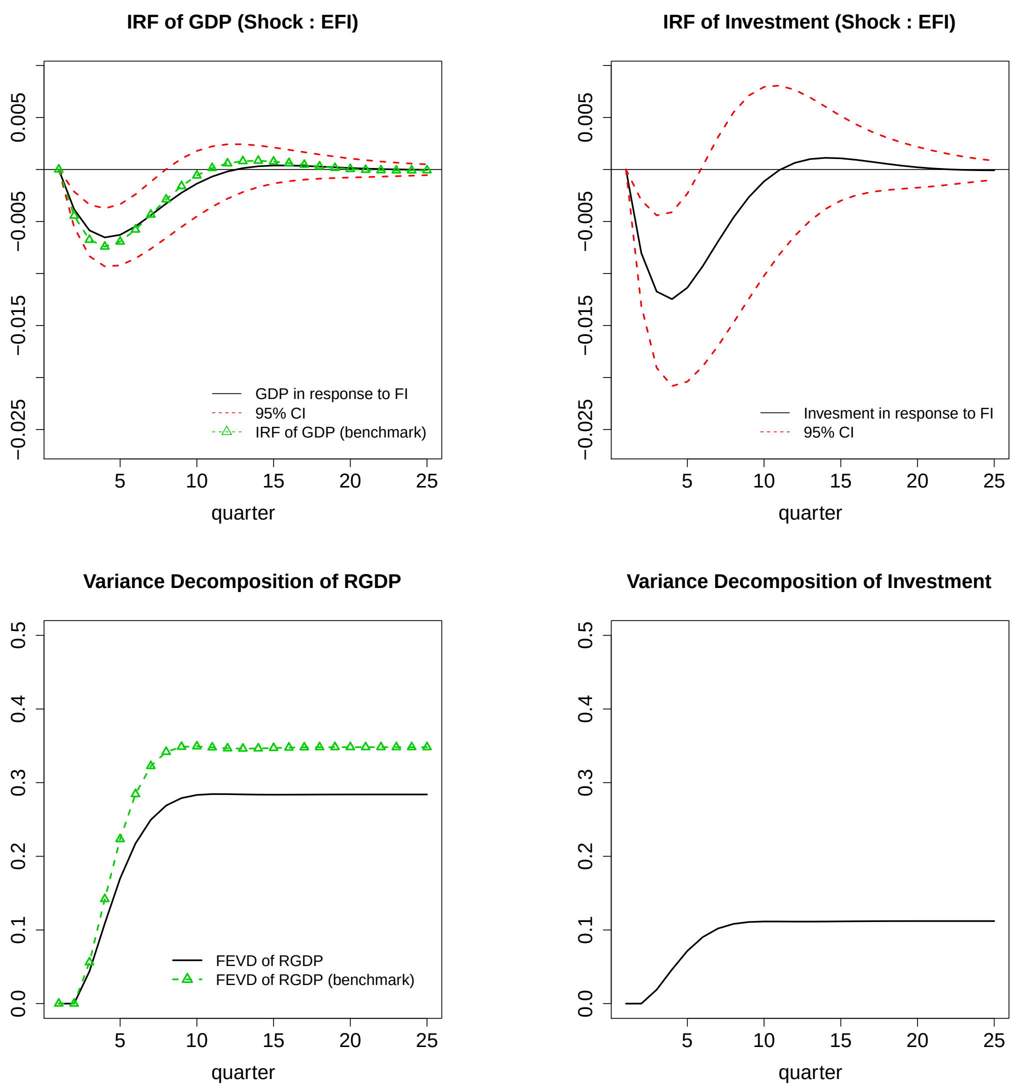
Notes: This figure shows gross issuance of international and domestic debt securities by country based on a nationality basis, as in Figure B.3, but scaling it by GDP. Data on quarterly gross issuance are scaled by annual GDP (i.e., the sum of last 4 quarters). Data on gross issuance are soured from Dealotic's DCM database and data on GDP are from the IMF International Financial Statistics Database. The regional aggregations are as follows: East Asia and Pacific: Indonesia, Korea, Malaysia, Philippines, and Thailand. East Europe and Central Asia: Czech Republic, Hungary, Poland, Russia, and Turkey. Latin America: Brazil, Chile, Colombia, Mexico and Peru. Other Regions: South Africa, and Israel.

Figure B.8: The Size of Non-financial and Financial Bonds



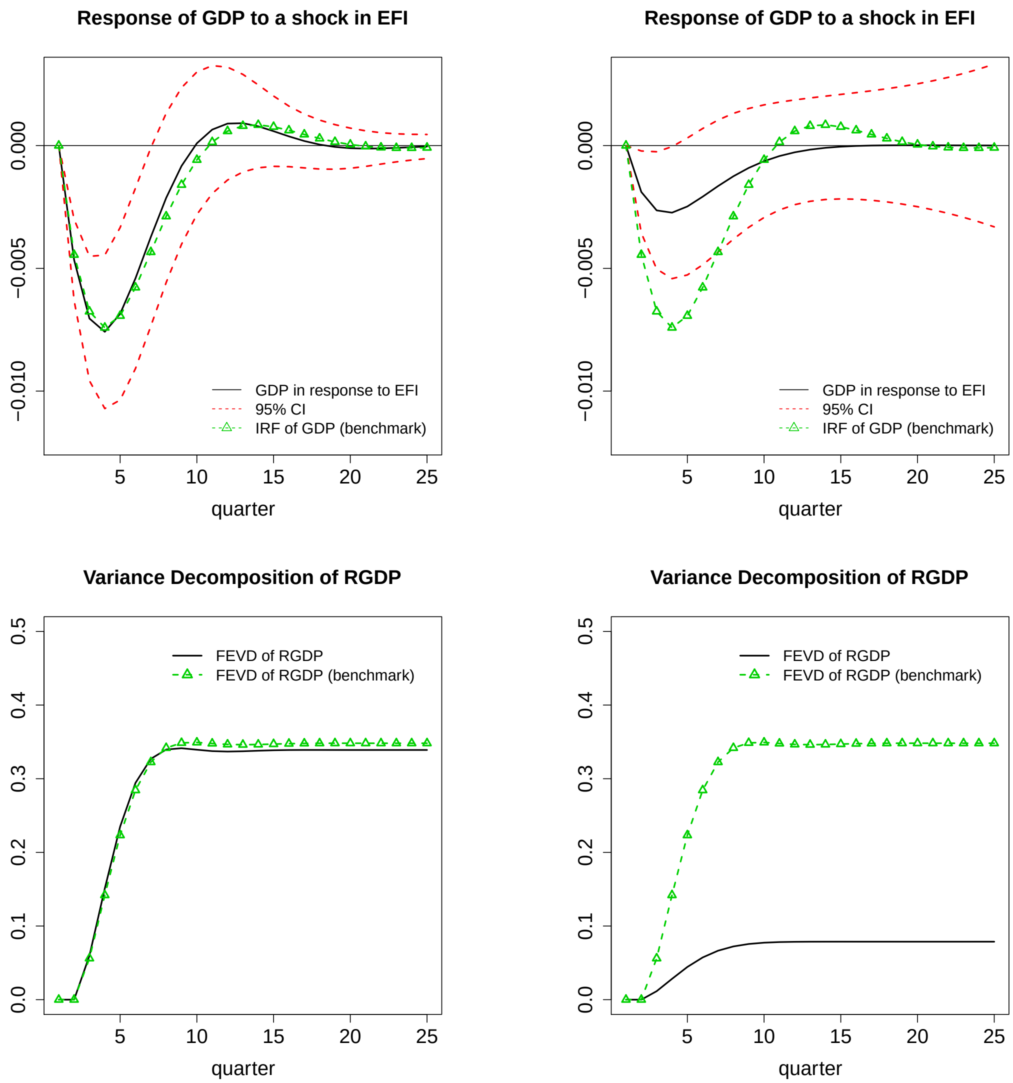
Notes: This figure shows the sum of the size of sample bonds (in 2003 Billion USD) used in constructing EFI, at a given quarter. The black solid line represents sum of both financial and non-financial bonds. The black dotted line only includes non-financial bonds (left-axis). The red solid line with triangles represents the fraction (right-axis) of non-financial bonds to total bonds. The top left panel represents aggregated statistics across countries, and other panels represents country-by-country statistics. As noted in Footnote 24, these figures show that the subsample of bonds with OAS data used in the paper is representative of the universe of bonds studied in Section 2.3 insofar as they depict a large increase in issuance after the 2008/2009 crisis.

Figure B.9: IRF and FEVD from the Uribe-Yue panel VAR



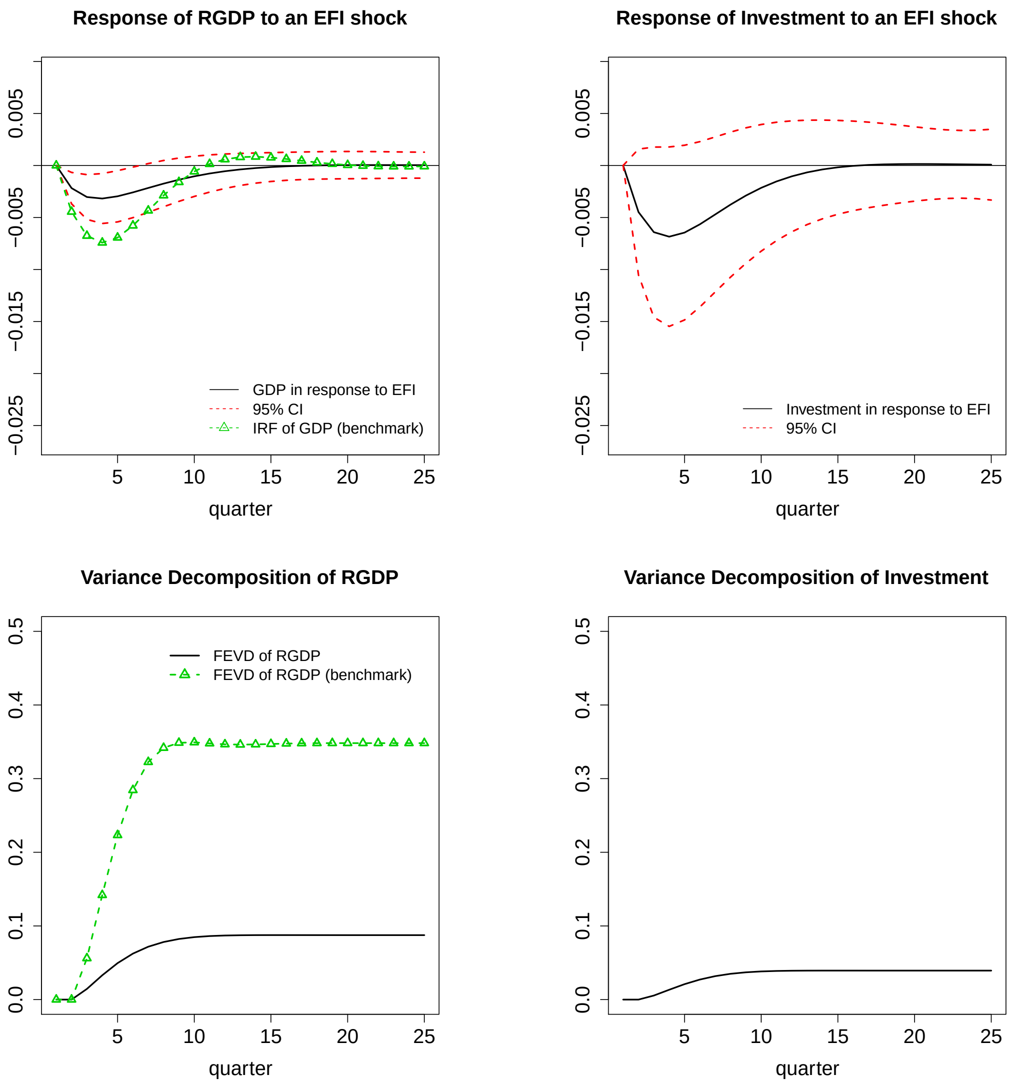
Notes: This figure summarizes impulse response functions and forecast error variance decompositions of a panel VAR model as in Uribe and Yue (2006). This model includes $\{\Delta GDP_{i,t}, \Delta Inv_{i,t}, \Delta Trade\,Balance_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta RFF_t\}$ as an exogenous variable. The top row presents an impulse response function of year-on-year real GDP, and investment growth rate to a 1 standard deviation shock in ΔEFI. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row summarizes forecast error decompositions of real GDP and investment growth rates. Green-triangle dotted lines represent results from Figure 2.4. Data for Malaysia starts in 2005.Q1 due to lack of investment data.

Figure B.10: Impulse Response Controlling for Sovereign and External Risk (Alternative Identifying Assumption)



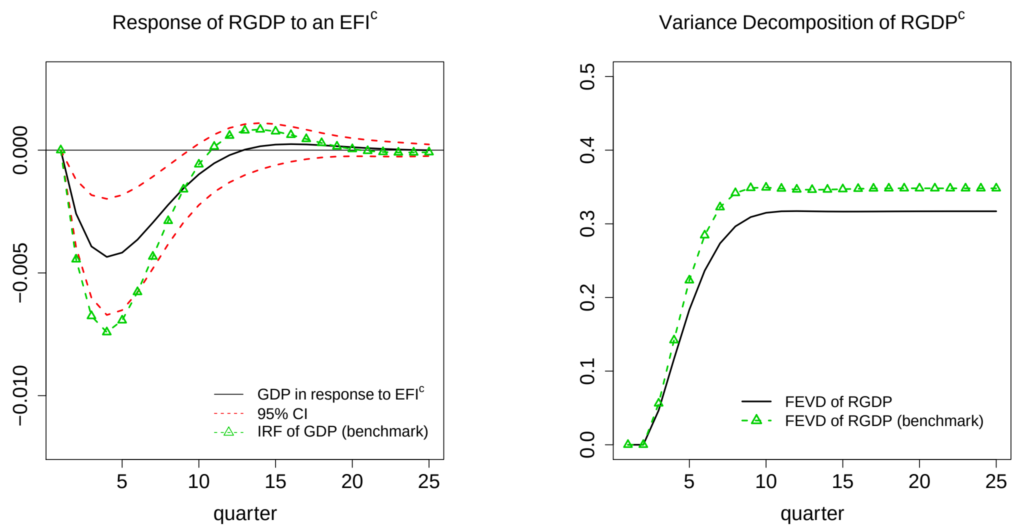
Notes: This figure reproduces results in Figure 2.6 with an alternative ordering in the Cholesky decomposition; $\Delta EMBI$ responds to ΔEFI only in lags. The first column shows results from a trivariate panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta EFI_{i,t}, \Delta EMBI_{i,t}\}$ as endogenous variables. The second column shows results from a trivariate panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta EFI_{i,t}, \Delta EMBI_{i,t}\}$ as endogenous variables, and $\{\Delta VIX_t\}$ as an exogenous variable. The top row presents an impulse response function of year-on-year real GDP to a 1 standard deviation shock in ΔEFI. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decomposition of real GDP associated with ΔEFI shocks. Green-triangle dotted lines represent results from Figure 2.4. Korea is excluded due to EMBI data availability. 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

Figure B.11: Alternative Panel VAR



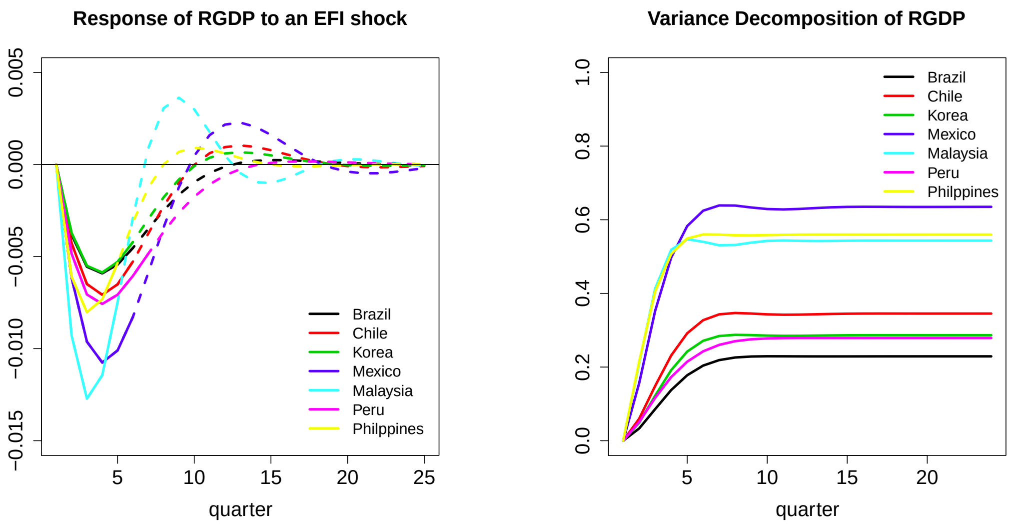
Notes: This figure summarizes impulse response functions and forecast error variance decomposition of the following panel VAR model which includes $\{\Delta GDP_{i,t}, \Delta INV_{i,t}, \Delta TB_{i,t}, \Delta EMBI_{i,t}, \Delta EFI_{i,t}\}$ as endogenous variables, and $\{\Delta RFF_t, \Delta VIX_t\}$ as exogenous variables. The top row presents an impulse response function of year-on-year real GDP, and investment growth rate to a 1 standard deviation shock in ΔEFI. Red dotted lines represent 95% confidence interval calculated using 500 draws of Monte Carlo simulations. The bottom row presents forecast error decomposition of real GDP and investment growth rates. Malaysian sample starts in 2005.Q1 due to investment data availability. Korea is excluded due to EMBI data availability. Green-triangle dotted lines represent results from Figure 2.4. 1999.Q2 EMBI observation for Chile is dropped due to EMBI data availability.

Figure B.12: IRF and FEVD with Benchmark Bi-variate Panel VAR with HP-filtered Variables



Notes: The two panels reproduce results from Figure 2.4 replacing ΔEFI and $GDP\,growth\,rate$ with EFI^c and ΔGDP^c respectively. The superscript c refers to variables filtered using the Hodrick-Prescott filter with a smoothing parameter of 1600. The left panel presents impulse response functions of $RGDP^c$ to a 1 standard deviation shock in EFI^c. The right panel presents a forecast error variance decomposition of real GDP growth rate. Green-triangle dotted lines represent results from Figure 2.4.

Figure B.13: Country-Specific Forecasting Regressions and SVAR



Notes: This figure summarizes impulse response functions and forecast error variance decompositions of the benchmark bivariate model estimated country by country. The plot on the left presents impulse response functions of year-on-year real GDP growth rate to a 1 standard deviation shock in ΔEFI. Solid lines represent the portion of the IRF that is significant portion at the 95% confidence level. The plot on the right panel row presents the fraction of forecast error variance of real GDP growth rate due to ΔEFI.

Table B.1: Share of International Loans to Sovereigns in Total International Bank Loans to EMEs

Year	Brazil	Chile	Colombia	Mexico	Peru
2006	5.21	0.00	1.74	0.00	0.01
2007	3.04	0.00	0.69	0.00	0.01
2008	2.77	0.00	1.49	0.00	0.44
2009	2.85	0.00	2.24	0.00	0.41
2010	1.61	0.00	0.00	0.00	0.24
2011	1.35	0.00	0.00	0.00	0.16
2012	1.53	0.00	0.13	0.00	0.11
2013	1.37	0.00	0.13	0.00	0.10
2014	1.06	0.00	0.55	0.00	0.08

Notes: This table shows the share of international loans to governments as percentage of all cross-border bank loans to the country for five emerging countries. Data on international bank loans to sovereigns are sourced from the LAC Debt Group Standardized Public Debt Database of the IDB and refer to the stock of outstanding bank loans under external legislation. Data on all cross-border bank loans are from the BIS Locational Banking Statistics and refer to stock of outstanding bank loans in a given country.

Table B.2: Currency Composition of International Debt Securities (on a nationality basis; as percentage of total)

		Local Currency		USD		ROW	
		2003-2008	2009-2014	2003-2008	2009-2014	2003-2008	2009-2014
EAP	Indonesia	5.39	13.42	92.38	83.89	2.23	2.70
	Korea	4.34	14.42	60.81	54.32	34.85	31.27
	Malaysia	24.63	66.10	71.86	23.56	3.50	10.34
	Philippines	4.90	18.81	95.10	81.19	0.00	0.00
	Thailand	2.23	6.57	91.88	91.03	5.90	2.40
ECA	Czech Rep.	13.59	15.02	22.63	13.84	63.78	71.14
	Hungary	2.94	5.75	0.00	16.27	97.06	77.98
	Poland	35.91	16.17	5.72	13.77	58.38	70.06
	Russia	39.92	56.28	49.73	34.68	10.36	9.05
	Turkey	7.03	7.32	81.11	84.33	11.86	8.35
LAC	Brazil	11.44	9.77	86.78	82.41	1.78	7.81
	Chile	4.53	5.46	93.41	83.61	2.06	10.93
	Colombia	4.19	9.87	95.81	90.13	0.00	0.00
	Mexico	47.05	13.87	40.85	68.86	12.09	17.27
	Peru	4.87	6.21	95.13	92.15	0.00	1.64
Other EM	Israel	23.00	44.06	70.29	53.14	6.71	2.80
	South Africa	54.56	28.72	16.18	54.95	29.25	16.34
Average		17.09	19.87	62.92	60.12	19.99	20.00

Notes: This table shows the currency composition of issuances of international debt securities by country based on a nationality basis. The data are sourced from Dealogic's DCM database. See Appendix B.1 a description of how the country aggregates are obtained from transaction-level data and for a definition of international debt securities.

Table B.3: Anderson-Hsiao Estimator

	(1) *Spec 1*	(2) *Spec 2*	(3) *Spec 3*	(4) *Spec 4*	(5) *Spec 5*
ΔGDP_t	0.20***	0.22**	0.21***	0.00046	0.10
	(4.02)	(2.04)	(3.66)	(0.00)	(0.98)
$\Delta\, EFI_t$	-0.000026***	-0.000025**	-0.000026***	-0.000017*	-0.000016*
	(-2.66)	(-2.53)	(-2.62)	(-1.84)	(-1.81)
$\Delta US\, Yield\, Curve_t$		0.00098			0.0015
		(0.63)			(0.95)
ΔRFF_t		0.000081			0.0011
		(0.07)			(1.13)
$\Delta R\, Local\ Rate_t$			0.00022		0.000025
			(0.34)		(0.03)
$\Delta R\, Pcom_t$				0.037***	0.036***
				(2.61)	(2.73)
Adjusted R^2	0.168	0.169	0.167	0.189	0.223
Observations	357	357	357	357	357

Notes: This table reproduces the baseline results of Table 2.2 using the Anderson-Hsiao estimator to address potential inconsistency of a LSDV estimator in a dynamic panel with fixed effects. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Table B.4: Country-Specific Forecasting Regressions

	Brazil	*Chile*	*Korea*	*Mexico*	*Malaysia*	*Peru*	*Philippines*
ΔGDP_t	0.76***	0.53***	0.73***	0.55***	0.45***	0.76***	0.64***
	(5.83)	(4.50)	(7.59)	(5.89)	(4.21)	(9.86)	(7.40)
$\Delta\, EFI_t$	-0.0000082	-0.000042	-0.000038***	-0.000027***	-0.00011***	-0.000017*	-0.000051***
	(-1.48)	(-1.64)	(-2.83)	(-3.37)	(-3.95)	(-1.87)	(-4.78)
$\Delta US\,Yield\,Curve_t$	0.0064***	-0.00059	0.0043**	-0.0028	-0.00039	0.0054**	-0.0014
	(3.47)	(-0.27)	(2.07)	(-1.16)	(-0.18)	(2.67)	(-1.02)
ΔRFF_t	0.0052***	0.0015	0.0032**	-0.000078	0.00019	0.00028	-0.00091
	(4.06)	(1.17)	(2.26)	(-0.07)	(0.12)	(0.23)	(-1.01)
$\Delta R\, Local\ Rate_t$	-0.00054	-0.0012	0.00066	-0.0013	0.0029**	0.0023**	0.000092
	(-0.74)	(-1.05)	(0.43)	(-1.24)	(2.29)	(2.47)	(0.20)
$\Delta R\, Pcom_t$	0.030*	0.021**	-0.0043	0.031***	0.031**	0.019*	-0.0033
	(1.98)	(2.30)	(-0.35)	(3.49)	(2.53)	(1.88)	(-0.47)
Adjusted R^2	0.711	0.720	0.732	0.865	0.798	0.764	0.718
Observations	53	53	53	53	53	53	53

Notes: This table reproduces Spec (5) in Table 2.2 estimating the regression on a country by country basis, as indicated at the top of each column. All variables are identically defined as in Table 2.2. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Table B.5: Panel Regression Results with Varying Number of Lagged Dependent Variables

	p=0	*p=1*	*p=2*	*p=3*
ΔGDP_t	0.75***	1.02***	0.97***	0.96***
	(21.42)	(17.51)	(17.31)	(15.41)
ΔGDP_{t-1}		-0.34***	-0.20***	-0.24***
		(-7.63)	(-4.34)	(-4.67)
ΔGDP_{t-2}			-0.12***	-0.0081
			(-7.89)	(-0.13)
ΔGDP_{t-3}				-0.10
				(-1.82)
$\Delta\, EFI_t$	-0.000022**	-0.000014**	-0.000013**	-0.000013**
	(-2.97)	(-2.86)	(-2.92)	(-3.09)
$\Delta US\,Yield\,Curve_t$	0.0032**	0.0016	0.0013	0.0013
	(2.66)	(1.57)	(1.32)	(1.35)
ΔRFF_t	0.0026**	0.0019**	0.0019**	0.0020**
	(2.67)	(2.82)	(3.10)	(3.13)
$\Delta R\,Local\ Rate_t$	0.00046	0.00029	0.00024	0.00028
	(0.86)	(0.77)	(0.65)	(0.73)
$\Delta R\,Pcom_t$	0.015*	0.012**	0.011**	0.011**
	(2.44)	(2.66)	(2.65)	(2.78)
Adjusted R^2	0.718	0.754	0.758	0.761
Observations	371	371	371	371

Notes: This table reproduces Spec (5) in Table 2.2 for alternatives values of p (the number of lags of ΔGDP). Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Table B.6: Panel Regression Results with Time Fixed Effect and Crisis Dummy Variable

	Spec 5	*Spec 6*	*Spec 7*	*Spec 8*	*Spec 9*	*Spec 10*
ΔGDP_t	0.75***	0.74***	0.74***	0.82***	0.74***	0.74***
	(21.42)	(17.27)	(18.08)	(17.08)	(16.17)	(16.89)
$\Delta\, EFI_t$	-0.000022**	-0.000021**	-0.000018**	-0.0000062	-0.0000062	-0.0000061
	(-2.97)	(-2.82)	(-2.77)	(-1.24)	(-1.18)	(-1.01)
$\Delta US\, Yield\, Curve_t$	0.0032**	0.0037**	0.0038**			
	(2.66)	(2.73)	(2.85)			
ΔRFF_t	0.0026**	0.0027**	0.0026**			
	(2.67)	(2.62)	(2.62)			
$\Delta R\, Local\, Rate_t$	0.00046	0.00048	0.00044			-0.000023
	(0.86)	(0.89)	(0.86)			(-0.04)
$\Delta R\, Pcom_t$	0.015*	0.014*	0.012*			-0.00017
	(2.44)	(2.20)	(2.18)			(-0.02)
$US\, \Delta GDP_t$		0.076	0.031			
		(1.31)	(0.53)			
Adjusted R^2	0.718	0.719	0.736	0.820	0.804	0.803
Observations	371	371	371	371	371	371
Country fixed effect	Yes	Yes	Yes	No	Yes	Yes
Crisis dummy	No	No	Yes	-	-	-
Time fixed effect	No	No	No	Yes	Yes	Yes

Notes: This table reports panel forecasting regression results with time fixed effect or a crisis dummy variable (1 if 2008.Q4, and 0 otherwise). The first column reports a baseline result (last column of Table 2.2). Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

Table B.7: Panel Regression Results with Time Fixed Effect and Crisis Dummy Variable and Alternative Forecasting Horizons

	h=1 ΔGDP_{t+1}	*h=2* ΔGDP_{t+2}	*h=3* ΔGDP_{t+3}	*h=4* ΔGDP_{t+4}	*h=0* ΔGDP_t
ΔGDP_{t-1}					0.73***
					(14.57)
ΔGDP_t	0.74***	0.45***	0.19*	-0.018	
	(16.89)	(6.84)	(2.42)	(-0.19)	
$\Delta\, EFI_t$	-0.0000061	-0.0000098*	-0.000013***	-0.000011	0.0000023
	(-1.01)	(-2.35)	(-4.22)	(-1.58)	(0.55)
$\Delta R\, Local\ Rate_t$	-0.000023	0.000065	0.0000088	-0.000027	-0.000040
	(-0.04)	(0.10)	(0.02)	(-0.08)	(-0.08)
$\Delta R\, Pcom_t$	-0.00017	0.011	0.026	0.029*	-0.0083
	(-0.02)	(0.85)	(1.69)	(1.98)	(-1.22)
Adjusted R^2	0.803	0.654	0.612	0.607	0.801
Observations	371	371	371	371	371
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes

Notes: This table reproduces the bottom panel of Table 2.4 (panel forecasting regression for different forecasting horizons h) including both time and country fixed effects. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

B.3 Controlling for Sovereign Risk with a Principal Component Analysis

As an alternative approach, we control for sovereign risk using a principal component analysis. First, we calculate principal components of ΔEFI and $\Delta EMBI$ at a country level. We assume that the first principal component denoted by $PC_{k,t}$ for country k measures the common component affecting ΔEFI and $\Delta EMBI$. We further construct new variables $\Delta EFI^{pc}_{k,t} \equiv \Delta EFI_{k,t} - PC_{k,t}$ and $\Delta EMBI^{pc}_{k,t} \equiv \Delta EMBI_{k,t} - PC_{k,t}$. In this framework, $\Delta EFI^{pc}_{k,t}$ captures the variation in $\Delta EFI_{k,t}$ which is independent from the sovereign risk.

The results of the regression are reported in the upper panel of Table B.8, where we reproduce the same five specifications of Table 2.3 while replacing ΔEFI and $\Delta EMBI$ with ΔEFI^{pc}, $\Delta EMBI^{pc}$, and PC. The coefficient associated with ΔEFI^{pc} continues to be negative, large in absolute value, and statistically significant at 5 percent.

Table B.8: Principal Component

	Spec 1	*Spec 2*	*Spec 3*	*Spec 4*	*Spec 5*
Panel A. Controlling for sovereign risk (Principal Component)					
$RGDP\,growth_t$	0.76***	0.83***	0.76***	0.66***	0.73***
	(27.38)	(21.54)	(29.17)	(11.42)	(16.83)
ΔEFI_t^{pc}	-0.000035**	-0.000035**	-0.000034**	-0.000028**	-0.000027***
	(-2.99)	(-3.98)	(-2.88)	(-3.08)	(-4.34)
$\Delta EMBI_t^{pc}$	0.0000078	0.000011	0.0000079	0.0000097	0.000013
	(0.48)	(0.77)	(0.48)	(0.64)	(1.05)
PC_t	-0.000025*	-0.000023*	-0.000025*	-0.000018	-0.000016
	(-2.15)	(-2.18)	(-2.24)	(-1.68)	(-1.69)
$\Delta US\,Yield\,Curve_t$		0.0023			0.0028*
		(1.76)			(2.18)
ΔRFF_t		0.0023*			0.0023*
		(2.18)			(2.35)
$\Delta R\,Local\,Rate_t$			0.00070		0.00041
			(1.08)		(0.66)
$\Delta R\,Pcom_t$				0.019**	0.020***
				(3.17)	(4.04)
Adjusted R^2	0.685	0.703	0.689	0.703	0.725
Observations	317	317	317	317	317
Panel B. Controlling for foreign investors' risk aversion (Principal Component)					
$RGDP\,growth_t$	0.72***	0.79***	0.72***	0.66***	0.73***
	(15.35)	(17.42)	(16.21)	(9.92)	(13.62)
ΔEFI_t^{pc}	-0.000019***	-0.000020***	-0.000019***	-0.000017***	-0.000018***
	(-5.86)	(-8.42)	(-5.73)	(-5.39)	(-6.11)
$\Delta EMBI_t^{pc}$	0.0000100	0.000013*	0.0000099	0.000011	0.000014*
	(1.34)	(2.39)	(1.21)	(1.29)	(2.10)
PC_t	-0.0000091	-0.0000078	-0.0000097	-0.0000075	-0.0000065
	(-1.28)	(-1.42)	(-1.30)	(-1.00)	(-0.99)
ΔVIX_t	-0.00053**	-0.00050***	-0.00050**	-0.00042**	-0.00037**
	(-3.70)	(-4.18)	(-3.60)	(-2.68)	(-2.65)
$\Delta US\,Yield\,Curve_t$		0.0023			0.0027*
		(1.90)			(2.14)
ΔRFF_t		0.0021*			0.0022*
		(2.39)			(2.45)
$\Delta R\,Local\,Rate_t$			0.00048		0.00029
			(0.82)		(0.48)
$\Delta R\,Pcom_t$				0.013**	0.015**
				(2.73)	(3.64)
Adjusted R^2	0.708	0.724	0.710	0.716	0.735
Observations	317	317	317	317	317

Notes: This table reproduces the Table 2.3 replacing ΔEFI and $\Delta EMBI$ with ΔEFI^{pc}, $\Delta EMBI^{pc}$, and PC. Numbers in parentheses are t-statistics adjusted for standard errors clustered by country. * indicates significance at 10 percent level, ** indicates significance at 5 percent level, and *** indicates significance at 1 percent level.

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