Signaling with Debt Currency Choice *

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Abstract

Firms in emerging markets borrow more in foreign currency when the local currency actually provides a better hedge in downturns. Motivated by this fact, we develop an international corporate finance model in which firms facing adverse selection choose the foreign currency share of their debt. In the unique separating equilibrium, good firms optimally expose themselves to currency risk to signal their type. Crucially, the nature of this equilibrium depends on the co-movement between cash flows and the exchange rate. We provide extensive empirical evidence consistent with this signaling channel and rule out alternative explanations using a detailed dataset including more than 4,800 firms in 19 emerging markets between 2005 and 2021. Our results have implications for evaluating and mitigating risks arising from currency mismatches in corporate balance sheets.

Keywords: Foreign currency debt, corporate debt, signaling, exchange rates

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1 Introduction

Many emerging market firms finance themselves with foreign currency debt. Yet foreign currencies, especially safe haven currencies, appreciate against the local currency during downturns. Many firms that borrow in foreign currencies are neither exporters nor do they employ currency hedges (e.g. Bräuning and Ivashina, 2020; Alfaro, Calani and Varela, 2022; Levin-Konigsberg, Stein, Averell and Castañon, 2023). The resulting currency mismatches amplify the impact of exchange rate shocks on firms, especially those in distress. This has been a recurring theme in emerging market crises. Corporate leverage and foreign currency borrowing, especially in dollars, have increased in recent years (Alfaro, Asis, Chari and Panizza, 2019; Maggiori, Neiman and Schreger, 2020; Eren and Malamud, 2022). Against this background, understanding the reasons why firms borrow in foreign currencies and expose themselves to currency risk is important.

Despite risks, foreign currency debt is also a potentially important source of funds for firms to grow, especially for those that are more productive (Salomao and Varela, 2022). While the literature on how foreign currency debt contributes to financial crises is large, analyzing micro-level trade-offs that firms face and the resulting cross-sectional allocations provides a promising new avenue for research. Our paper provides an explanation rooted in information asymmetries and makes a theoretical and empirical contribution to this nascent literature.

We first document that corporates borrow more in foreign currencies when the local currency would actually provide a better hedge. In particular, we show that in countries for which the co-movement of the returns on the local currency sovereign bond and the stock market is greater (i.e., local currency provides a better hedge against downturns),[1] the average foreign currency share of the emerging market corporates is larger. This observation is puzzling as it suggests that firms for which foreign currency borrowing is riskier borrow even more in foreign currency. We also document that firms tend to issue more debt in foreign currencies when the local currency cash flow volatility is greater.

[1]Given data limitations, constructing measures of local currency corporate bond return is difficult. Nevertheless, the literature has found considerable co-movement between sovereign yields and corporate yields (e.g. Mendoza and Yue, 2012; Bedendo and Colla, 2015; Bevilaqua, Hale and Tallman, 2020), making sovereign yields good reasonable proxies in our calculation.

Motivated by these facts, we develop an international corporate finance model in which firms facing adverse selection choose the composition of their debt in local and foreign currency. Our model is set up as a one-dimensional signaling game. A firm with private information about its future cash flows needs to finance investment with debt denominated in local and foreign currencies. Both the exchange rate and the cash flow are random variables. The firm chooses the fraction of foreign currency debt to maximize its expected profit. Risk-neutral, rational creditors offer price schedules conditional on firms' choice of foreign currency debt share, reflecting firms' default risk.

We show that, under natural conditions, a unique separating equilibrium exists featuring a monotonic relationship between the foreign currency share and the hidden firm quality. The fraction of foreign currency debt perfectly reveals the firm's hidden ability to generate earnings. In this equilibrium, good firms expose themselves to greater currency risk to signal their type to investors. The intuition behind this result is similar to that in the standard pecking order theory: A default due to an adverse foreign currency appreciation shock is less likely for good firms. Better firms take on greater risk to differentiate themselves in the presence of asymmetric information than they would in a perfect information setting, raising the funding cost. However, overall funding costs of better firms remain lower compared to others within the separating equilibrium as firm types and default probabilities are fully revealed to investors.

Our model, therefore, also provides a rationale for why emerging market firms do not generally hedge currency exposures. Anecdotally, Ivashina, Kostas and Zogbi (2018) report a statement by Advent LatAm managers, a global private equity firm: "We [Advent] have never hedged; it is too expensive. The only hedge we have is growth." The statement fits well with the mechanism in our model, where firms expose themselves to currency risk to signal their quality or growth potential to investors.

A crucial implication of the model that sets our theory apart from other alternative explanations is that the nature of this equilibrium depends crucially on the co-movement between the foreign currency/local currency exchange rate and the firm's cash flows: If the foreign currency exchange rate is negatively related to firm's cash flows, that is cash flows fall when the local currency depreciates, then higher foreign currency debt signals a good type, *and vice versa*. While the former is the case for many emerging market economy firms, this dichotomy is a distinctive prediction of our theory, which we test empirically.

We present a body of empirical results that links exchange rate-cash flow co-movements, foreign currency share in borrowing, and firm performance. Using a detailed dataset on the debt structure of firms in 19 emerging market economies, we show that both levels and changes in the foreign currency debt share predict firm performance, leveraging the rich panel structure of the dataset as well as using large local currency depreciation episodes as event studies. We show that the predictive power of foreign currency debt on future performance is stronger for younger firms and unrated firms where one would expect information asymmetries to be more relevant. Importantly, we also find evidence for the distinctive key prediction of the theory, namely a dichotomy between firms with positive and negative co-movement between cash flows and exchange rates. As a whole, this evidence is consistent with the predictions of our model, and alternative explanations cannot account for the full set of results.

We construct a comprehensive firm-level dataset for our empirical analysis using Capital IQ, S&P Global Market Intelligence. This database includes detailed information on the individual debt instrument level that a firm has on its balance sheet, which includes bank loans and bonds. We aggregate this data to generate our main variable of interest, the foreign currency share, and match it to balance sheet data, income statements, and firms' stock returns. This exercise gives us a firm-level yearly panel dataset for more than 4,800 firms in 19 emerging market economies between 2005 and 2021.

We first focus on firms for which cash flows co-move negatively with the dollar, which we call "negative beta" firms. This is the case for a large majority of firms in our sample. Leveraging the panel structure, we use a battery of fixed effects (country-industry-time interaction fixed effects and firm fixed effects) and firm-time level information to single out both the level and the changes of foreign currency share of debt as predictors of better future performance (i.e., higher earnings before interest and taxes normalized by assets). Focusing only on firms within a given country and industry in a given time period allows us to rule out potential time-varying differences across countries or industries affecting the results. We also control for other variables that are identified in the literature as alternative ways through which firms might signal in the presence of adverse selection, which helps us isolate the effect of foreign currency borrowing as a signaling channel. We also show that among negative beta firms, those with a greater foreign currency debt share perform better during large local currency depreciation episodes.

Focusing first on negative beta firms, we rule out several other alternative explanations through a number of other tests and robustness checks. In our baseline regressions, we restrict attention to firms that have at least once borrowed in foreign currencies to rule out any confounding factors related to market access. To rule out any potential cash-flow hedges firms might have from exporting that might affect the results, we restrict the sample to only include firms in non-tradable sectors, and the results remain robust. We also show that our results hold when we restrict the sample to only firms with domestic parents. In additional robustness checks, we focus only on firms that have borrowed in foreign currencies in a given year. Finally, we show that the predictive power of foreign currency debt is stronger for firms where one would expect information asymmetries to matter more, such as younger firms and firms that have not received a public credit rating.

Crucially, in line with the key prediction of the signaling channel, we show a dichotomy between positive and negative beta firms since these firms expose themselves to currency risk differently. Better negative beta firms signal by borrowing more in foreign currency, while better positive beta firms signal by borrowing more in local currency, exposing themselves to currency risk. In the data, indeed, higher foreign currency share predicts worse performance for positive beta firms, in stark contrast to negative beta firms. The existence of such a dichotomy lends strong support to the signaling motive.

In the presence of information asymmetries, currency mismatches help firms reveal their types to investors, but such signals are costly, as is generally the case in models of signaling (Spence, 1973). In the model, this leads to heterogeneous UIP deviations across the distribution of firms in the form of credit risk premia. This is another unique prediction of our model. Importantly, this is a prediction at the level of the firm and, hence, regardless of what country-level UIP deviations based on risk-free rates are. Using the available information on the prices of firms' debt within our dataset and controlling for various factors, including country-industry-time fixed effects, we also provide evidence for such deviations in line with the predictions of our model.

All in all, our results point toward a novel channel of why firms expose themselves to currency risk. Previous literature has resorted to exogenously given country-level UIP deviations to explain this phenomenon. In our paper, in the presence of information asymmetries, firms have incentives to signal their quality to their creditors by taking on exchange rate risks arising from currency mismatches. Hence, we do not rely on exogenous country-level UIP deviations to explain why firms take on currency risk, which naturally leads to different policy implications. Our results highlight a more nuanced view of the risks arising from foreign currency borrowing. Firms that take on exchange rate risks might indeed be better placed to have these risks on their balance sheets. However, since they are exposed to currency risk, large exchange rate shocks might nevertheless put them in distress. In other words, signaling allows better firms to differentiate themselves from others, but it is risky and costly. Our results also suggest that policies that aim at reducing information asymmetries, such as more transparency or better disclosure requirements, would mitigate corporate risk-taking through currency mismatches in emerging market economies.

Related literature Our paper mainly contributes to several strands of literature, both theoretically and empirically. There is a nascent literature on the cross-sectional heterogeneity in firms' choices leading to currency mismatches, which can have implications in the aggregate. We explore a signaling channel in the face of adverse selection and provide broad evidence for many emerging market economies. In doing so, we also contribute to strands of literature that analyze firm borrowing in foreign currencies and risks arising from resulting currency mismatches. We also contribute to the literature on capital structure choice by considering two types of debt in an international setting and providing an empirical investigation.

The closest papers to ours are by Salomao and Varela (2022), Du, Pflueger and Schreger (2020), and Eren and Malamud (2022). We describe how our paper differs from these papers and how it complements them in detail below.

Salomao and Varela (2022) build a model with heterogeneous firms to analyze the trade-offs in firms' currency debt decisions and assess the distribution of foreign loans and its aggregate consequences in a setup without information asymmetries. There are three major differences between our approaches. First, we model information asymmetries. A novel key mechanism that affects currency mismatches in our model is signaling, which is in addition to and competes with the traditional risk management motive present in their model.[2] Second, in their model, firms borrow in foreign currency to take advantage of country-level UIP deviations, while we do not assume any cost advantages. In fact, in our model, at the firm level, foreign-currency borrowing becomes more expensive than local-currency borrowing for firms whose cash flow co-moves inversely with the local currency exchange rate due to costly signaling, for which we provide empirical evidence. Third, our empirical analysis covers firms in 19 emerging market economies, while their paper focuses only on a single country (Hungary).

We provide an in-depth comparison between our model and the model of Salomao and Varela (2022) in Appendix D and link the predictions of both models with the empirical patterns presented in our paper. In particular, based on simulated data from Salomao and Varela (2022), we show that conditioning on productivity, firms reduce exposure to foreign-currency debt when exchange rate and idiosyncratic productivity become more volatile and when the cash flow-exchange rate correlation becomes more negative (which is at odds with the evidence we provide in the next section (Figure 1(b))). We also demonstrate that their model fails to replicate our empirical finding that a higher foreign-currency debt share predicts higher future earnings.

Du, Pflueger and Schreger (2020) show that governments tend to borrow in currencies that appreciate in bad times rather than in local currency, which provides a hedge. They argue that governments resort to foreign currency borrowing to alleviate the commitment problem of deflating their local currency debt through inflation. While the mechanisms that drive their results, such as lack of commitment in setting monetary policy, apply to sovereigns, they do not directly apply to corporates. Our signaling model offers a different but related mechanism applied to corporates

[2] Phan (2017) develops a theoretical model of sovereign debt as a signaling device. In this model, the sovereign can only observe the realization of productivity shocks, while foreign investors can only observe its distribution. Similar papers include Cole, Dow and English (1995) and Sandleris (2008). In our model of currency choice, the lenders make decisions only based on the foreign currency share of issuance. We also provide empirical support for the signaling channel of currency choice.

rooted in information asymmetries, and we provide evidence using firm balance sheets at the micro level.

Eren and Malamud (2022) develop a capital structure model in which firms choose the currency composition of their debt in a symmetric information setting where debt is issued for its tax benefits. Empirically, they are mainly interested in why global firms borrow in dollars instead of other reserve currencies. In contrast, in this paper, we aim to understand why emerging market firms borrow in foreign currencies instead of their local currency. They derive conditions under which all firms issue debt in a dominant currency, which depends on the co-movement of the exchange rate and cash flows. This statistic also plays a crucial role in our paper. The trade-off theory in Eren and Malamud (2022) applies to large, established international firms with diversified cash flows and minimal adverse selection costs (see also Nikolov, Schmid and Steri (2021)). By contrast, the theory developed in the current paper is better suited for emerging market firms with a significant degree of informational asymmetry.

Our paper is also related to the literature that studies currency mismatch on corporate balance sheets and its impact during severe emerging market currency depreciation. Several theoretical and empirical papers study the emergence and implications of currency mismatch (e.g. Jeanne, 2003; Caballero and Krishnamurthy, 2003; Aguiar, 2005; Kim, Tesar and Zhang, 2015; Niepmann and Schmidt-Eisenlohr, 2021; Kohn, Leibovici and Szkup, 2020; Du and Schreger, 2022). Our paper provides information on how cross-sectional firm heterogeneity could impact the emergence and consequences of currency mismatches with empirical applications from several emerging market currency depreciation episodes and a broad dataset covering multiple emerging market economies. Our results also suggest a more nuanced view of local currency depreciation episodes. Firms with foreign currency debt are better positioned to weather these shocks since they are firms with greater quality.

Another strand of the literature studies why firms, especially in emerging markets, borrow in safe-haven currencies, especially the dollar, in the first place. Jiang, Krishnamurthy and Lustig (2021) and Koijen and Yogo (2020) estimate a dollar convenience yield arising from investor safety demand, lowering borrowing costs in dollars. Gopinath and Stein (2020) argue that dollar invoicing creates a demand for dollar deposits, leading to cheaper dollar loans. Using data from Peru, Gutiérrez, Ivashina and Salomao (2022) show that investor demand for safety lowers the dollar deposit rate that banks pass through to loans, making them cheaper for borrowers (see also di Giovanni, Kalemli-Özcan, Ulu and Baskaya (2021) for evidence from Turkey). Taking dollar discount as given, Bruno and Shin (2017), Caballero, Panizza and Powell (2016), and Acharya and Vij (2022) show that the propensity to borrow in dollars increases when carry trade is more profitable.[3] In our model, firms borrow in safe-haven currencies to signal their quality and voluntarily expose themselves to currency risks. Therefore, currency mismatches can still arise without a motive for carry trade or cost advantages.

We also contribute to the literature on capital structure choice by analyzing different types of debt in an international setting when firms face adverse selection. In the pecking order theory (Myers and Majluf, 1984), debt is a preferred means of financing because it is less sensitive to adverse selection than equity.[4] The optimality of debt in the presence of asymmetric information has been established in numerous papers. Several papers also empirically evaluate the pecking order theory (see, for example, Franck and Goyal (2003), Helwege and Liang (1996), and Leary and Roberts (2010)) or test the signaling theory in the data (Eckbo, Giammarino and Heinkel, 1990). To our knowledge, we are the first to provide an international pecking order theory with two types of debt (local and foreign currency) and empirically test it. Developing this theory is technically challenging and has required developing novel mathematical techniques for tackling the signaling problem in a multi-dimensional setting.

Our model has three state variables: The firm's hidden type (known ex-ante), the exchange rate shock, and the cash flow shock (both realized ex-post). It turns out that the optimal signaling policy depends extremely subtly on the joint covariance structure of these three variables. Verifying

[3]Other papers study firms' choice in borrowing in dollars versus euros. Eren and Malamud (2022) show that the dollar provides a better hedge than the euro during global downturns. Caramichael, Gopinath and Liao (2021) compare borrowing costs in the dollar and the euro with and without currency hedges. Coppola, Krishnamurthy and Xu (2022) argue that when asset markets are illiquid, firms denominate their debt in the currency of the most liquid public asset.

[4]While this logic still holds in dynamic settings with short-term private information (see Hennessy, Livdan and Miranda (2010)), this intuition breaks down with the dynamic arrival of long-term information. See, for example, Morellec and Schuerhoff (2011), who show informational asymmetries may not translate into a clear pecking order over securities when investment timing serves as a signaling device. See also Grenadier and Malenko (2009).

the second-order conditions then reduces to establishing non-trivial inequalities for the correlations of optimal policies with shocks. To the best of our knowledge, no such signaling problems have been studied in the literature before.

2 Motivating evidence: Corporate local currency debt share and local currency debt risk

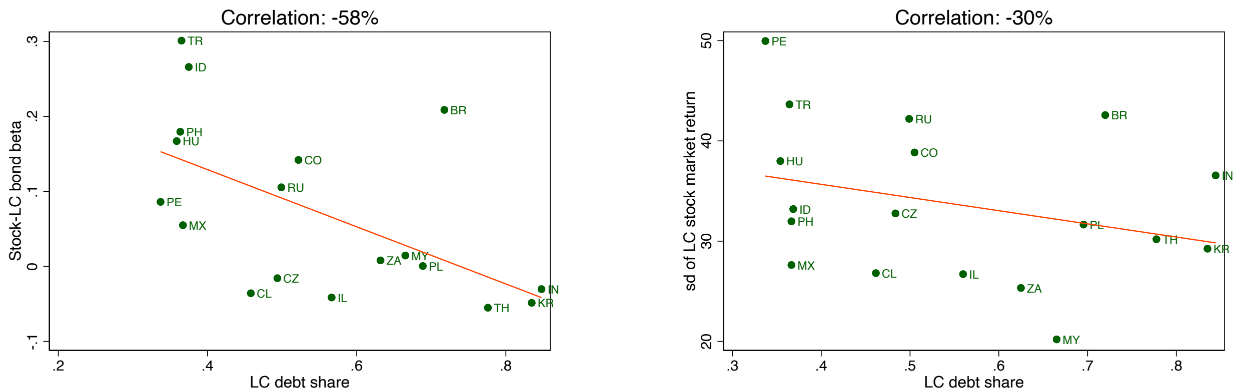
Using aggregate cross-country data, we document two empirical relationships related to emerging market firms' funding currency choice.[5] First, we use the government local currency bond-stock beta, computed as in Du, Pflueger and Schreger (2020, henceforth DPS), and show the correlation of local currency share in the aggregate corporate borrowing and the government local currency bond-stock beta. Our results are similar to those of DPS for government debt. Given data limitations, constructing local currency corporate bond return measures is difficult. Nevertheless, the literature has found considerable co-movement between sovereign yields and corporate yields (Mendoza and Yue, 2012; Bedendo and Colla, 2015; Bevilaqua, Hale and Tallman, 2020). As a result, we believe the government's local currency bond-stock beta is a good proxy for the hedging properties for local currency corporate debt. In a subsequent exercise, we compute the volatility of local-currency stock market return – a measure of the cash-flow uncertainty of emerging market corporates – and relate this measure to the currency choice of emerging market corporates.

Bond-stock beta and corporate local currency share First, we examine the relationship between corporate local currency bond issuance and the hedging benefits of a local currency bond. Following DPS, we define the country i-specific local-currency bond-stock beta as the coefficient β of the following regression:

$$xr^{LC}_{i,n,t} = \alpha_i + \beta(bond_i, stock_i) \times xr^{m}_{i,t} + \varepsilon_{i,t}\,. \tag{1}$$

[5] In the empirical analysis, we use data for firms from 19 emerging market economies. In these aggregate figures, we drop Argentina due to the unavailability of reliable data on LC bond spread.

Figure 1: EM financial correlates of corporate local currency debt shares



(a) Stock-local currency bond beta

(b) Stock return volatility

Note: Panel (a) shows the local currency stock-local currency bond beta of the central government debt versus average corporate local currency debt share for 18 emerging market economies over the sample period 2005-2021. Panel (b) plots the within-year standard deviation of overlapping quarterly local currency stock market return against corporate local currency debt share, with both measures averaged over the sample period 2005-2021. Source for corporate local currency debt share: Capital IQ. Sources for stock price, exchange rate, and bond yields: BIS, Bloomberg, and Refinitiv.

In this equation, $xr^{LC}_{i,n,t}$ is the log quarterly excess return on local currency long-term bond over domestic short rate (3-month T-bill):

$$xr^{LC}_{i,n,t+1} = r^{LC}_{i,n,t+1} - y^{LC}_{i,1,t}/4\,,$$

and $r^{LC}_{i,n,t+1}$ is the quarterly log holding period return on local currency long-term bond:

$$r^{LC}_{i,n,t+1} \approx \tau_{i,n,t} y^{LC}_{i,n,t} - (\tau_{i,n,t} - 1/4)\underbrace{y^{LC}_{i,n-1,t+1}}_{\approx y^{LC}_{i,n,t+1}}.$$

On the right-hand side, the excess local-currency stock market return is defined as the log quarterly return on the local equity market, denoted $r^m_{i,t+1}$), over log local currency T-bill:

$$xr^m_{i,t+1} = \underbrace{(p^m_{i,t+1} - p^m_{i,t})}_{r^m_{i,t+1}} - y^{LC}_{i,1,t}/4\,.$$

We obtain local currency government bond yields and stock market indices from Bloomberg. Also, following DPS, we focus on the 5-year tenor for local currency bond, so that $\tau_{i,n,t} = 5$ and $n = 20$.

Local currency bond excess return over T-bill captures the cost of government financing. In bad times, stock market return is low (SDF/marginal utility of consumption is high). A *positive* beta corresponds to the case in which local currency bond excess return goes down in bad times, reducing the value of debt repayments for domestic borrowers so that local currency bonds are good hedging instruments.

Figure 1(a) compares local currency bond-stock beta and local currency share in total corporate debt (from Capital IQ), averaged from 2005 to 2021. Compared to DPS, we restrict attention to EM countries, but we also find a strong negative correlation. Firms whose home countries' government debt has a better hedging property during downturns issue relatively less local currency-denominated debt, forgoing the hedging benefits of local currency. DPS rationalizes a similar pattern for government debt by offering a theory of risk-averse lenders and governments' limited commitment to inflation. However, our similar observation in the context of corporate borrowing remains puzzling.[6]

Stock return volatility and local currency share of corporate debt A large literature has established the role of information asymmetry and barriers to information transmission in determining capital inflows to emerging markets (see, for example, Bekaert (1995) and Portes and Rey (2005)). Cash-flow uncertainty, measured by stock return volatility, could serve as a rough indicator.[7] To complement our previous finding, we ask if our observation potentially leads to an explanation based on information asymmetry. After computing the within-year standard deviation of overlapping quarterly aggregate local-currency stock market return ($r^m_{i,t+1}$), we plot this measure (averaged over 2005 to 2021) against EM corporates' local-currency debt share in Figure 1(b). EM firms tend to issue more foreign-currency debt when the local currency-denominated cash flow becomes more uncertain, with a correlation coefficient of -0.3.

[6]Figure C1 in Appendix C shows that this relationship also holds if we use firm-level data to calculate $\beta(bond_i, stock_i)$ instead for each firm. In particular, Figure C1 plots the market-cap weighted binscatters and finds a similar correlation between firm-level stock-bond beta and local currency share.

[7]Past empirical and theoretical literature highlight the role of private information on stock return volatility. See French and Roll (1986).

3 Model

Motivated by the empirical relationships documented in Section 2, we develop an international corporate finance model in which firms facing adverse selection choose the composition of their debt in local and foreign currency. In such an environment, if firms' cash flows are lower during local currency depreciation episodes, borrowing in foreign currency debt is risky, *and vice versa*. We show that, under natural conditions, a unique separating equilibrium exists in which the fraction of foreign currency debt is a signal that perfectly reveals the firm's type. Better firms effectively take on the FX risk through currency mismatches to reveal their quality to investors. Hence, our theory also provides a rationale for why emerging market firms do not typically hedge their currency mismatches.

3.1 Setup

There are two time periods, $t = 0, 1$. A cash-poor firm has an investment project with a fixed investment cost of I. It can only finance this project with nominal debt, denominated in local or foreign currency (for simplicity in exposition, we use \$ in the notations below to refer to foreign currency). At the time $t = 1$, when the cash flows X of the firm and the foreign-currency exchange rate $\varepsilon = LC/FC$ are realized, the firm pays out its debt if cash flows are sufficient. Otherwise, it defaults. For simplicity, we assume that the recovery rate in default is zero. We also assume that the foreign-currency exchange rate at $t = 0$ equals 1.

Debt markets suffer from a standard adverse selection problem: The firm has a hidden type $\mu \in \mathbb{R}$ that is known to the firm at time $t = 0$ but not to the creditors. The creditors try to filter the firm's type from its debt issuance policy. We denote by B and $B_\$$, respectively, the face values of the firm's local and foreign currency-denominated debt. Then, the total face value in local currency to be paid back to debt-holders is given by $B + \varepsilon B_\$$. We use $\alpha = B_\$/B$ to denote the quotient of the face values. Similarly, P and $P_\$$ denote the prices of local currency- and foreign currency-denominated debt of the firm with a face value equal to one unit of the respective currency. Since the firm issues debt to finance its investment, the budget constraint takes the form

$$I \;=\; B\,P \;+\; B_{\$}\,P_{\$} \;=\; B\,(P \;+\; \alpha\,P_{\$})\,. \tag{2}$$

Defining $\bar{P} \;\equiv\; P \;+\; \alpha\,P_{\$}$, we get

$$B \;=\; I/\bar{P}\,.$$

Since the face value B is pinned down by the budget constraint, the only information available to creditors is that in α, the foreign currency-share of total debt face value. Hence, the interest rates $1/P$ and $1/\bar{P}$ offered by creditors depend on this single variable. In the sequel, we therefore use the notation $P(\alpha),\ P_{\$}(\alpha),\ \bar{P}(\alpha),\ B(\alpha),\ B_{\$}(\alpha)$. We need the following technical assumption.

Assumption 1 *The random vector (X,μ,ε) of firm cash flows, hidden type, and exchange rate have a joint densify $\rho(x,\mu,\varepsilon)$ on $(0,+\infty)\times[\mu_0,\bar{\mu}]\times[\varepsilon_*,\varepsilon^*]$, where ε^* could be infinite.*

We also use $\eta(x|\mu,\varepsilon)$ to denote the density of X conditional on μ,ε. We assume that η is log-concave in x and has the standard monotone likelihood property: $(\log\eta)_\mu \;=\; \frac{\eta_\mu}{\eta}$ is monotone increasing in x. That is, firms of higher type μ have higher cash flows.

As one can see, our model has three state variables: The firm's hidden type, the exchange rate shock, and the cash flow shock. Below, we show how to derive the optimal policy in such a complex, multi-dimensional environment. We prove that the verification of second-order conditions is equivalent to establishing inequalities for the correlations of optimal policies with shocks. These inequalities are non-trivial. To the best of our knowledge, no standard techniques exist for analyzing such multi-dimensional signaling problems.

The monotone likelihood property guarantees that an increase in μ leads to a first-order stochastic dominance shift in the distribution of X, so that higher μ means a better firm. See Lemma B.2 in the Appendix. All proofs are relegated to Appendix B. We use

$$\Phi(x,\mu,\varepsilon) \;=\; \int_0^x \eta(y|\mu,\varepsilon)dy$$

to denote the cumulative distribution function of the firm's cash flows conditional on (μ, ε), and

$$\Psi(x, \mu, \varepsilon) \;=\; \int_x^\infty (y - x)\eta(y|\mu, \varepsilon)dy$$

to denote the expected cash flows above a level x, conditional on (μ, ε).

Lenders offer firms price schedules based on α. We assume that all market participants are risk-neutral and fully rational and discount future at zero rates. Under this assumption, the bond price schedules are given by

$$P(\alpha) \;=\; E[(1 - \Phi(Z(\alpha, \varepsilon), \mu, \varepsilon))|\alpha],\; P_{\$}(\alpha) \;=\; E[\varepsilon(1 - \Phi(Z(\alpha, \varepsilon), \mu, \varepsilon))|\alpha]$$

because the firm defaults if and only if cash flows X are below the total debt face value, as given by

$$Z(\alpha, \varepsilon) \;\equiv\; B(\alpha) + \varepsilon B_{\$}(\alpha) \;=\; (1 + \alpha\varepsilon)B(\alpha) \;=\; (1 + \alpha\varepsilon)I/\bar{P}(\alpha)\,, \tag{3}$$

with $\bar{P}(\alpha) = P(\alpha) + \alpha P_{\$}(\alpha)$. As we do not restrict the exchange rate a priori, we do not assume that foreign currency borrowing has an inherent cost advantage, so that country-level UIP deviations is irrelevant to our mechanism. We also note that, conditional on α, shareholders' equity value is given by

$$E[\Psi(Z(\alpha, \varepsilon), \mu, \varepsilon)]\,.$$

3.2 Characterization of the equilibrium

We focus our analysis on fully revealing, separating equilibria.[8] In this class of equilibria, lenders internalize the issuance decision of the firms by offering price schedules $P(\alpha)$ and $P_{\$}(\alpha)$ based on the anticipated firms' type. In other words, α perfectly signals the firm's hidden type μ for those firms that are able to raise enough funds to finance I. To allow for rationing, we study monotone

[8] As is well-known, signaling models often feature multiple equilibria. We focus on the class of separating equilibria, following DeMarzo and Duffie (1999). The results of our empirical analysis in Section 4 suggest that the separating equilibrium is indeed the relevant equilibrium in the data.

threshold rationing equilibria in which all firms of type μ above an equilibrium threshold μ_* get financing.[9]

Definition 3.1 *A separating monotone equilibrium (henceforth, equilibrium) is given by*

- *a rationing threshold* $\mu_* \geq \mu_0$*;*
- *a strictly monotone, continuously differentiable function* $A(\mu):\ [\mu_*, \bar{\mu}] \ \rightarrow\ \mathbb{R}_+$ *defining the fraction of foreign-currency debt issued by the firm of type* μ *with the inverse function* $\mu(\alpha)$ *such that:*
  - *if* A *is monotone increasing, then* $\mu(\alpha):\ [\alpha^*, +\infty]\ \rightarrow\ [\mu_*, \bar{\mu})$ *such that* $\mu(\alpha_*) = \mu_*,\ \mu(\infty) = \bar{\mu}$
  - *if* A *is monotone decreasing, then* $\mu(\alpha):\ [0,\ \alpha^*]\ \rightarrow\ [\mu_*, \bar{\mu})$ *such that* $\mu(0) = \bar{\mu},\ \mu(\alpha^*) = \mu_*$
- *out-of-equilibrium beliefs: for firms that choose* $\alpha < \alpha^*$ *in the increasing equilibrium or* $\alpha > \alpha^*$ *in the decreasing equilibrium, creditors believe that they have a type* $\mu = \mu_*$*.*[10]
- *debt pricing functions are rational and satisfy*

$$P(\alpha) \ = \ E[(1-\Phi(Z(\alpha,\varepsilon),\mu(\alpha),\varepsilon))],\ P_{\$}(\alpha) \ = \ E[\varepsilon(1-\Phi(Z(\alpha,\varepsilon),\mu(\alpha),\varepsilon))]\,, \tag{4}$$

  where $\mu(\alpha) \ = \ A^{-1}(\alpha)$ *if the inverse of* $A(\mu)$*;*
- *the fraction* $A(\mu)$ *is optimal for the firm given the debt pricing functions (4):*

$$A(\mu) \ = \ \arg\max_{\alpha>0} E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu,\varepsilon)]\,. \tag{5}$$

  and

$$\max_{\alpha>0} E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu,\varepsilon)] \ \geq \ I$$

[9] We only consider equilibria in which all pricing functions are continuously differentiable with respect to α.

[10] This assumption ensures that it is never optimal for a firm to choose α outside the respective interval.

if and only if $\mu \geq \mu_*$.

Note that there is complete symmetry between the foreign currency and local currency in our model. Indeed, instead of ε, consider $\tilde{\varepsilon} \equiv \varepsilon^{-1}$, the FC/LC exchange rate, and let $\tilde{X} \equiv X/\varepsilon$ be the firm cash flows denominated in foreign-currency. By direct calculation, the conditional density of $\tilde{X}$ is given by $\tilde{\eta}(\tilde{x}|\mu,\tilde{\varepsilon}) = \tilde{\varepsilon}^{-1}\eta(\tilde{\varepsilon}^{-1}\tilde{x}|\mu,\tilde{\varepsilon})$ and we can similarly define the functions $\tilde{\Phi}$ and $\tilde{\Psi}$:

$$\tilde{\Phi}(\tilde{x},\mu,\tilde{\varepsilon}) = \int_0^{\tilde{x}} \tilde{\eta}(y|\mu,\tilde{\varepsilon})dy$$

and

$$\tilde{\Psi}(\tilde{x},\mu,\tilde{\varepsilon}) = \int_{\tilde{x}}^{\infty} (y-\tilde{x})\tilde{\eta}(y|\mu,\tilde{\varepsilon})dy\,.$$

We can also define

$$P_*(\tilde{\alpha}) = E[(1-\tilde{\Phi}(Z(\alpha,\tilde{\varepsilon}),\mu,\tilde{\varepsilon}))|\tilde{\alpha}],\ P_{\$,*}(\tilde{\alpha}) = E[\tilde{\varepsilon}^{-1}(1-\Phi(Z(\tilde{\alpha},\tilde{\varepsilon}),\mu,\tilde{\varepsilon}))|\tilde{\alpha}]$$

and

$$\tilde{P}(\tilde{\alpha}) = P_{\$,*}(\tilde{\alpha}) + \tilde{\alpha}P_*(\tilde{\alpha}) = E[\tilde{\varepsilon}^{-1}(1+\tilde{\alpha}\tilde{\varepsilon})(1-\Phi(Z(\tilde{\alpha},\tilde{\varepsilon}),\mu,\tilde{\varepsilon}))]\,,$$

with

$$Z(\tilde{\alpha},\tilde{\varepsilon}) = \tilde{B}_{\$}(\tilde{\alpha})(1+\tilde{\alpha}\tilde{\varepsilon})\,.$$

In particular, $\tilde{P}(\tilde{\alpha}) = \tilde{\alpha}\bar{P}(\tilde{\alpha}^{-1})$. Furthermore,

$$I = \tilde{B}(\tilde{\alpha})P_*(\tilde{\alpha}) + \tilde{B}_{\$}(\tilde{\alpha})P_{\$,*}(\tilde{\alpha}) = \tilde{B}_{\$}(\tilde{\alpha})\tilde{P}(\tilde{\alpha})\,,\ \textit{and}\ \tilde{B}_{\$}(\tilde{\alpha}) = I/\tilde{P}(\tilde{\alpha})\,.$$

Then, we can rewrite the firm's objective as

$$\max_{\tilde{\alpha}>0} E[\tilde{\varepsilon}^{-1}\tilde{\Psi}((1+\tilde{\alpha}\tilde{\varepsilon})I/\bar{P}(\tilde{\alpha}),\mu,\tilde{\varepsilon})]\,.$$

This symmetry will allow us to always have a local currency counterpart for every result of foreign-currency debt.[11]

We construct a candidate equilibrium using first-order conditions and then verify that the candidate equilibrium satisfies all the necessary technical conditions. First, we note that (4) immediately implies that

$$\bar{P}(\alpha) \;=\; E[(1+\varepsilon\alpha)(1-\Phi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon))\,. \tag{6}$$

Define $F(x,y)$ implicitly to be the unique[12] solution to

$$x \;=\; E[(1+\varepsilon y)(1-\Phi((1+\varepsilon y)I/x,\; F(x,y),\; \varepsilon))]\,.$$

Then, (6) yields the following result.

Lemma 3.2 *In a separating equilibrium, the inverse $\mu(\alpha)=A^{-1}(\alpha)$ of the optimal policy is given by*

$$\mu(\alpha) \;=\; F(\bar{P}(\alpha),\,\alpha)\,.$$

We now derive an equation for $\bar{P}(\alpha)$. To this end, we use the first order conditions for the firm in (5): At an interior optimum of $\max_\alpha E[\Psi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]$, we get that the first order condition defining the candidate optimum $\alpha=A(\mu)$ is given by

$$-E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))(B'(\alpha)(1+\varepsilon\alpha)+B(\alpha)\varepsilon)] \;=\; 0\,,$$

and, in equilibrium, this condition must hold for $\mu \;=\; F(\bar{P}(\alpha),\,\alpha)$. Substituting $B(\alpha) \;=\; I/\bar{P}(\alpha)$ and using (6), we can characterize the equilibrium price of debt.

Proposition 3.3 *In any candidate equilibrium, the price $\bar{P}(\alpha)$ satisfies the ordinary differential*

[11] We provide more details on the symmetry in Appendix A.

[12] Uniqueness follows because, by the monotone likelihood property, Φ is monotone decreasing in μ.

equation

$$\bar{P}'(\alpha) \;=\; E[\varepsilon(1-\Phi((I/\bar{P}(\alpha))(1+\varepsilon\alpha), F(\bar{P}(\alpha),\,\alpha),\varepsilon))]\,, \tag{7}$$

and the corresponding candidate equilibrium $\mu(\alpha)$ *is given by* $\mu(\alpha) \;=\; F(\bar{P}(\alpha),\,\alpha)\,.$

We can derive sufficient conditions for monotone equilibria with equation (7). Intuitively, a firm's decision to issue foreign-currency debt will depend on the risk profile of ε – whether foreign-currency appreciation is associated with higher (respectively, lower) expected cash flows. Reducing currency mismatches is consistent with the traditional hedging motive – doing so would reduce the probability of default due to debt revaluation. However, in a separating equilibrium, taking on currency mismatches potentially leads to better financing conditions as creditors respond to the revealed types of higher-quality firms.

Recall that $\tilde{\varepsilon} = \varepsilon^{-1}$, $\tilde{X} \;\equiv\; X/\varepsilon$, and $\tilde{\eta}(\tilde{x}|\mu,\tilde{\varepsilon}) \;=\; \tilde{\varepsilon}^{-1}\eta(\tilde{\varepsilon}^{-1}\tilde{x}|\mu,\tilde{\varepsilon})$ The following proposition confirms that the signaling motive could dominate in equilibrium.

Proposition 3.4 *The following is true.*

- *if* $(\log\tilde{\eta})_{\tilde{\varepsilon}\tilde{x}} \;<\; 0$*, then any candidate equilibrium* $\mu(\alpha)$ *from Proposition 3.3 is monotone decreasing in* α*;*
- *if* $(\log\eta)_{\varepsilon x} \;<\; 0$*, then any candidate equilibrium* $\mu(\alpha)$ *from Proposition 3.3 is monotone increasing in* α*.*

Furthermore, in any equilibrium, firm equity value

$$E(\mu) \;\equiv\; E[\Psi((1+A(\mu)\varepsilon)I/\bar{P}(A(\mu)),\mu,\varepsilon)] \tag{8}$$

is monotone increasing in μ*.*

The conditions of Proposition 3.4 are best understood with the example of a joint Gaussian distribution. If (x,ε) are jointly normally distributed, then $x|\varepsilon \sim N(\bar{x}+\beta\varepsilon,\sigma^2)$, where the sign of β coincides with that of $\mathrm{Cov}(x,\varepsilon)$. Thus, by direct calculation, $(\log\eta(x,\varepsilon))_{x\varepsilon} = (-0.5(x-(\bar{x}+\beta\varepsilon))^2/\sigma^2)_{x\varepsilon} = \beta/\sigma^2$. As a result, $(\log\eta(x,\varepsilon))_{x\varepsilon} < 0$ implies a negative correlation between x and

ε. In this case, foreign-currency appreciation is associated with lower expected cash flows. This is the typical situation for many emerging market firms. These firms, according to Proposition 3.4, would choose to voluntarily forgo their natural hedges and borrow in foreign currency if their hidden types are sufficiently high to allow them to generate higher cash flows. Lemma 3.5 provides a method to construct the equilibrium we characterized:

Lemma 3.5 *The unique candidate monotone decreasing equilibrium (that is, an equilibrium in which high α signals a bad type) is constructed as follows. First, using $\mu(0) = \bar{\mu}$ we find $\bar{P}(0)$ as the unique solution to*

$$\bar{P}(0) \;=\; E[(1 - \Phi(I/\bar{P}(0), \bar{\mu}, \varepsilon)] \, .$$

Then, $\bar{P}(\alpha)$ is defined as the unique solution to the ODE (7). And then, α^* is defined as the unique solution to

$$E(\mu(\alpha^*)) \;=\; I \, ,$$

where $E(\mu)$ is defined in (8). In the monotone increasing equilibrium, we first do the transformation to $\tilde{\alpha} = 1/\alpha$ and then proceed as above.

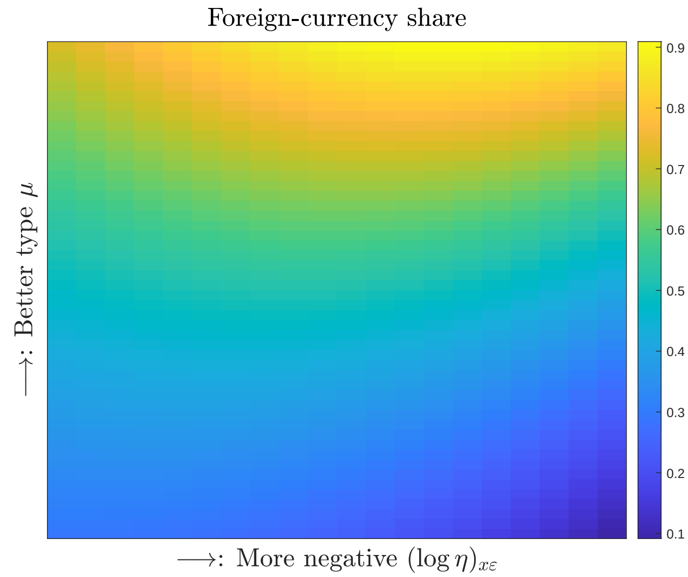
Guided by Lemma 3.5, Figure 2 plots the equilibrium fraction of foreign currency as a function of both the hidden types of firms and firms' cash flow sensitivity to the exchange rate. For illustration, we focus on the increasing equilibrium and assume the conditional cash flow is log-normally distributed with condition mean given by $f(\mu, \varepsilon) = \mu - \delta \log \varepsilon$ with $\delta > 0$. A higher value of δ thus leads to a more negative covariance between cash flows and foreign currency appreciation.[13]

Figure 2 numerically displays the equilibrium forces at work. Consistent with our model prediction, firms with better types always borrow more in foreign currency. The traditional hedging motive still exists in our model: firms with low types would like to reduce borrowing in foreign currency if local currency depreciation leads to a larger decline in future cash flows. However, with adverse selection, the firm's hedging motive is outweighed by the incentive to signal a high repayment ability, effectively reducing the firm's debt burden ex-ante. Under our parametric

[13]We assume that $\eta(x|\mu, \varepsilon) \;=\; \frac{1}{\sqrt{2\pi}\sigma x} e^{-(\log x - f(\mu,\varepsilon))^2/(2\sigma^2)}$, so that $(\log \eta)_{x\varepsilon} = x^{-1} f_\varepsilon(\mu, \varepsilon)/\sigma^2 = -(\varepsilon x)^{-1}\delta/\sigma^2$.

assumption, firms with a sufficiently high type borrow even more in foreign currency even as its cash flow becomes more sensitive to local currency depreciation.[14]

Figure 2: Foreign-currency share, sensitivity to depreciation, and firm type



Note: This figure numerically illustrates the equilibrium foreign currency share as a function of the hidden type and cash flow sensitivity to the exchange rate. The colors on the heatmap represent equilibrium foreign-currency shares chosen by firms of type μ under different values of $(\log \eta)_{x\varepsilon}$. We focus on an increasing equilibrium and assume cash flows are conditionally log-normal with parameters $(\mu_\varepsilon, \sigma_\varepsilon)$: $\eta(x|\mu, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma x} e^{-(\log x - f(\mu,\varepsilon))^2/(2\sigma^2)}$. with the conditional mean function given by $f(\mu, \varepsilon) = \mu - \delta \log(\varepsilon), \delta \in [1, 2]$. A higher δ corresponds to a more negative $(\log \eta)_{x\varepsilon}$, thus a larger cash flow sensitivity to local currency depreciation. The unconditional distribution of the exchange rate is also assumed to be log-normal. Foreign-currency share is expressed as a fraction (from zero to one) by transforming the face value ratio α using the transformation $(\alpha^{-1} + 1)^{-1}$. Parameter values are given by: $\varepsilon_* = e^{-1}, \varepsilon^* = e^1, \mu_\varepsilon = 0.2, \sigma_\varepsilon = 0.2, \sigma = 0.1, I = 0.5$.

To complete the analysis, we need to verify the second-order conditions of the firm. We impose mild restrictions to ensure that the candidate optimum satisfying the first-order conditions is indeed the true global optimum. It turns out that these second-order conditions can be described explicitly in terms of the dependence of the conditional density η on (μ, ε).

Proposition 3.6 *The following is true.*

[14] In the Appendix, we show that our model can numerically replicate the positive correlation between realized stock return volatility and foreign-currency share documented by Figure 1(b) at the aggregate level. See Figure C2. Appendix Figure C3 plots the equilibrium quantities as functions of foreign-currency share corresponding to the parameter values used in Figure 2.

- *if* $(\log \eta)_{x\varepsilon} \leq 0$ *and* $(\log \tilde{\eta})_{\tilde{x}\tilde{\varepsilon}} \geq 0$ *and* $(\log \tilde{\eta})_{\mu\tilde{\varepsilon}} \geq 0$, *then any candidate equilibrium is monotone increasing in* α *and is a true equilibrium;*

- *if* $(\log \tilde{\eta})_{\tilde{x}\tilde{\varepsilon}} \leq 0$ *and* $(\log \eta)_{x\varepsilon} \geq 0$ *and* $(\log \eta)_{\mu\varepsilon} \geq 0$, *then any candidate equilibrium is monotone decreasing in* α *and is a true equilibrium.*

Finally, to connect the model with our empirical analysis, we prove a theoretical result about the link between ex-ante and ex-post sensitivity of the stock price to the exchange rate. Consider the expected equity value conditional on the realization of the exchange rate shock ε. It is given by $\Psi(B(\alpha)(1+\varepsilon\alpha), \mu(\alpha), \varepsilon)$. The following result shows that the sign of the co-movement between equity value and ε coincides with that of the cash flows, as captured by the sign of $\log \eta_{x\varepsilon}$.

Proposition 3.7 *If* $\log \eta_{x\varepsilon} > 0$ *then*

$$\frac{\partial}{\partial \varepsilon} \Psi(B(\alpha)(1+\varepsilon\alpha), \mu(\alpha), \varepsilon) \ > \ 0 \, ,$$

and the sign changes to negative when $\log \tilde{\eta}_{\tilde{x}\tilde{\varepsilon}} > 0$.

4 Empirical evidence

In this section, we provide a body of empirical results testing the main predictions of our theory. The signaling channel of foreign currency borrowing predicts that firms optimally expose themselves to currency risk to signal their quality to investors. Crucially, another novel prediction is that signaling properties of foreign currency debt depend on whether firms' cash flows co-move negatively or positively with the value of the foreign currency - the dollar in our empirical setting. Firms whose cash flows are negatively correlated with the dollar (i.e., negative beta firms) signal their quality to investors by borrowing *more* in foreign currency. On the other hand, firms with a positive cash flow co-movement with the dollar (i.e., positive beta firms) signal their quality by borrowing *less* in foreign currency. In the presence of information asymmetries, currency mismatches help firms reveal their types to investors, but such signals come at a cost. This leads to firm-level credit UIP deviations, which are independent of any country-level UIP deviations. Using the available information on the prices of firms' debt within our dataset, we also provide evidence that aligns with our model's predictions. While the body of results we provide is consistent with the predictions of our theory, and alternative explanations can rationalize some individual results, we are unable to come up with an alternative hypothesis that can also account for the entirety of our results.

We structure this section as follows. First, we describe the dataset that is relatively underused in the literature, highlight its novel uses in our setup, and report relevant summary statistics. Building up from granular outstanding debt data, we construct measures corresponding to those in the model. Next, we focus on negative beta firms, those with negative cash-flow co-movement with the dollar, as these firms constitute a large majority of our sample. Leveraging the panel structure, we use a battery of fixed effects (Country$\times$Industry$\times$Year$\times$Quarter and Firm) and firm-time level information to single out both the level and the changes of foreign currency share of debt as predictors of future performance. We rule out several alternative explanations through several robustness checks. We also show that negative beta firms with a greater foreign currency debt share performed better during significant local currency depreciation episodes, a counter-intuitive result that can be explained through our model. Further results suggest that the predictive power of foreign currency debt for future firm performance is stronger for younger firms and unrated firms, for which information frictions arguably matter more. In addition, we show that in line with the distinctive prediction of the theory, there is a dichotomy between positive and negative beta firms since these firms expose themselves to currency risk differently. Higher foreign currency share predicts worse performance for positive beta firms in stark contrast to negative beta firms. Finally, we show that the behavior of firm-level credit UIP deviations is consistent with our theoretical prediction.

4.1 Data and summary statistics

We obtain firm-level balance sheet information from the S&P Capital IQ database. In its debt capital structure module, Capital IQ reports outstanding debt instruments issued by a global set of firms and provides information on the type, principal due, coupon rate, maturity, and repayment currency of each security. Compared with other firm-level datasets on global debt issuance, Capital

IQ tracks the stock of outstanding debt on each firm's balance sheet and includes a wide range of securities beyond external bond issuance and syndicated borrowing.[15]

We focus on non-financial firms from 19 major emerging market economies with flexible exchange rate regimes using yearly data between 2005 and 2021.[16] The empirical counterpart to α in Section 3 is the foreign-currency debt outstanding as a share of total outstanding debt reported in the debt capital structure module. For firm f in year t, the foreign-currency share of its outstanding debt, $foreign\ currency\ share_{f,t}$, is defined as

$$foreign\ currency\ share_{f,t} = \frac{\sum_{i \neq LC} Debt\ Outstanding_{i,f,t}}{\sum_i Debt\ Outstanding_{i,f,t}} * 100$$

where $Debt\ Outstanding_{i,f,t}$ is firm f's outstanding debt denominated in currency i, and LC denotes local currency. We also define "hard-currency" share analogously as the share of outstanding debt denominated in a set of advanced economy currencies (USD, GBP, CHF, EUR, and JPY).

Our model establishes a strong link between the cash flow sensitivity of firms to exchange rate shocks and firms' foreign-currency borrowing. Proposition 3.7 further shows that the direction of the co-movement between cash flows and the exchange rate in the model can be measured by the sensitivity of stock prices to exchange rate shocks. To calculate firm-level β between stock return and local currency depreciation, we merge our sample with monthly firm-level stock price information obtained from Thompson Reuters Worldscope (via ISIN) and country-level bilateral exchange rate against the U.S. dollar from the BIS.

For each period t and each firm, the stock return-depreciation β is estimated by regressing overlapping quarterly stock return on quarterly local currency depreciation against the U.S. dollar, within a recursive window up to time t.[17] To form our baseline sample for predictive panel regressions, we compute Newey-West standard errors and test the (one-sided) null hypothesis that the β is statistically less or equal to zero.

[15] Kim (2019), Kim, Mano and Mrkaic (2020) and Du and Schreger (2022) also use Capital IQ data to construct currency breakdown of outstanding corporate debt at the firm and country level.

[16] The countries are Argentina, Brazil, Chile, Colombia, Czech Republic, Hungary, Indonesia, Israel, India, Korea, Mexico, Malaysia, Peru, Philippines, Poland, Russia, Thailand, Turkey, and South Africa.

[17] We estimate the rolling β using monthly stock prices and exchange rates. To alleviate the concern about small-sample biases, the minimum recursive window size is set to be 48 months. For windows narrower than 48 months, we impute the β using the estimates from the 48-month window if possible. The average window size is 102 months.

We construct our predictive regressions using a large set of firm-level financial variables. Firm-level outcomes include earnings before interest and taxes (EBIT), normalized by total assets, and log capital expenditures. The firm-specific information set includes yearly stock returns, market cap (from Worldscope), Altman z-score, firm size proxied by total liabilities, the current level of log capex, and current ratio, defined as total current assets divided by total current liabilities. We winsorize the financial variables at 2.5% and 97.5% to alleviate the impact of outliers.

Table 1 reports summary statistics.[18] According to Panel (a), the average foreign-currency share of total debt is 15%, mostly comprised of hard currencies. Panel (b) reports statistics on the estimated rolling-βs. Consistent with intuition, over 90% of observations have a negative correlation between stock return and local currency depreciation. Moreover, for most of the positive-β observations, we cannot reject the null hypothesis (at 5% level) that the β is less than or equal to zero. Table 2 checks if the firms in our sample differ along the dimension of foreign-currency borrowing (α) and cash flow sensitivity to the exchange rate (β). Consistent with prior literature, Panel (a) suggests that, on average, firms that borrow in foreign currency tend to be larger (measured by total assets or earnings). Meanwhile, they are financially less stable than their peers who only borrow in local currency, as indicated by a relatively smaller current ratio and z-score. Panel (b) compares an average firm with a positive stock return-depreciation β to an average firm with a negative β. Firms with a negative β are, on average, slightly larger than positive-β firms but have a relatively smaller current ratio and z-score. Positive-β firms, on average, have a larger foreign currency share out of total debt, consistent with the idea that these firms may have operational hedges.

[18] Table C8 reports summary statistics for our main regression sample to be defined in the next section. The main takeaway is similar.

Table 1: Summary statistics

Panel (a): Financial variables and foreign-currency share

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
foreign currency share (%)	103206	15.17	29.448	0	100	0
hard currency share (%)	103206	11.506	26.745	0	100	0
fc share (bank loan, %)	95245	16.497	31.361	0	100	0
EBIT / total assets (%)	102996	4.498	9.899	-32.482	27.796	5.047
log total asset (mil. USD)	103196	4.857	2.003	-8.061	12.921	4.708
log total liabilities (mil. USD)	103205	4.091	2.143	-7.201	12.109	3.973
current ratio	103178	1.926	1.833	.133	11.612	1.395
z-score	97066	2.834	2.743	-1.989	13.283	2.254
annual stock return (%)	96905	18.549	69.562	-71.429	260.082	.897
log capex (mil. USD)	99425	1.254	2.66	-13.633	10.824	1.311
log market cap (mil. USD)	99906	4.199	2.178	-4.343	13.133	4.031

Panel (b): Stock return-depreciation beta for each firm

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
negative betas	93500	-1.881	1.997	-148.824	0	-1.478
positive betas	9706	.897	1.859	0	42.46	.462
positive betas, insignificantly > 0	8565	.749	1.553	0	36.912	.397

Note: This table reports summary statistics for the key variables used in the empirical analysis. Panel (a) focuses on firm-level balance sheets. Foreign currency share is the share of outstanding debt denominated in currencies other than a firm's local currency. Hard currency is defined as one of CHF, EUR, GBP, JPY, or USD. Bank loan contains two types of instruments: term loans and credit lines. The current ratio is defined as the ratio between current assets and current liabilities. The financial variables are winsorized at 2.5% and 97.5%. Panel (b) reports summary statistics for the stock return-depreciation betas. For each firm, monthly observations from Worldscope are used to regress overlapping quarter-over-quarter stock returns on quarter-over-quarter local currency depreciation against the U.S. dollar. The rolling betas are generated using all available information from 2000 and a recursive window. β insignificantly larger than zero refers to observations for which we cannot reject the null hypothesis that they are less or equal to zero, with confidence intervals computed using Newey-West standard errors.

Table 2: Firm characteristics by foreign-currency share or sign of β

Panel (a): by zero or positive foreign-currency share

	zero fc share		**non-zero fc share**		**mean diff.**
	mean	sd	mean	sd	t
EBIT / total assets (%)	4.13	(10.35)	5.20	(8.93)	-16.61
log total asset (mil. USD)	4.29	(1.76)	5.94	(1.99)	-136.81
log total liabilities (mil. USD)	3.46	(1.91)	5.29	(2.05)	-142.01
current ratio	2.08	(2.04)	1.64	(1.30)	36.70
z-score	3.05	(2.97)	2.43	(2.22)	33.76
annual stock return (%)	19.28	(71.50)	17.21	(65.83)	4.42
log market cap (mil. USD)	3.67	(1.99)	5.18	(2.18)	-110.37
log capex (mil. USD)	0.55	(2.47)	2.56	(2.50)	-121.83
β (negative)	-1.98	(2.18)	-1.69	(1.58)	-21.25
β (positive)	0.94	(1.93)	0.81	(1.71)	3.35
β (positive, insignificantly > 0)	0.76	(1.45)	0.71	(1.75)	1.38
Observations	67714		35492		103206

Note: See notes after Panel (b) for details on definitions of indicators.

4.2 Evidence on negative beta firms

In this section, we focus on negative beta firms as they comprise a significant dataset share.[19] A negative co-movement of cash flows and the dollar exchange rate means that these firms are worse off when the dollar appreciates. According to our model, firms have incentives to take on this risk by borrowing more in foreign currency to signal their quality to their investors in the presence of asymmetric information. In what follows, we test if firms with a higher level or change in foreign currency share of debt perform better. We present evidence in line with the model's

[19]Since these beta coefficients are estimated variables, in the results reported in the main text, we categorize firms with negative beta as those for which the null hypothesis that β is less than or equal to zero is not rejected at a 5% confidence level. We compute the confidence interval using Newey-West standard errors with three lags. Those for which it is rejected are classified as positive beta firms. We report the results with the classification using only the coefficient estimates without hypothesis testing in the Appendix (see Table C1). The results are largely similar.

predictions, first using the panel structure and then restricting the sample to only episodes of large local currency depreciation.

Table 2: Firm characteristics by foreign-currency share or sign of $\boldsymbol{\beta}$ (continued)

Panel (b): By the sign of β

	$\boldsymbol{\beta < 0}$		$\boldsymbol{\beta > 0}$		$\boldsymbol{\beta > 0}$, insignificant	
	mean	sd	mean	sd	mean	sd
EBIT / total assets (%)	4.62	(9.71)	3.27	(11.49)	3.12	(11.52)
log total asset (mil. USD)	4.91	(1.99)	4.31	(2.00)	4.27	(1.95)
log total liabilities (mil. USD)	4.15	(2.14)	3.48	(2.11)	3.46	(2.04)
current ratio	1.91	(1.82)	2.09	(1.97)	2.08	(1.96)
z-score	2.80	(2.70)	3.16	(3.09)	3.13	(3.08)
annual stock return (%)	18.41	(69.30)	20.01	(72.13)	19.85	(72.08)
log market cap (mil. USD)	4.23	(2.19)	3.94	(2.08)	3.89	(2.02)
log capex (mil. USD)	1.31	(2.65)	0.73	(2.72)	0.68	(2.68)
foreign currency share (%)	14.96	(29.13)	17.20	(32.25)	16.35	(31.59)
Observations	93500		9706		8565	

Note: Panel (a) of Table 2 compares balance sheet indicators between firms with zero or positive foreign-currency borrowings. Foreign currency share is the share of outstanding debt denominated in currencies other than a firm's local currency. Panel (b) makes the comparison among firms with positive stock return-depreciation βs versus firms with negative βs as well as firms with positive βs insignificantly larger than zero from a one-sided t-test using Newey-West standard errors. The βs are computed using monthly data on overlapping three-month stock return (obtained from Worldscope) and a three-month local currency depreciation (obtained from BIS). The financial variables are winsorized at 2.5% and 97.5%.

4.2.1 Panel data analysis

We use our dataset's panel structure and test whether a firm's foreign currency share of liabilities at a given period can predict the "hidden" information on firms' quality. We map the theory to data by testing whether foreign currency borrowing predicts future performance measured by earnings before interest and taxes normalized by assets, i.e., $\frac{\text{EBIT}}{\text{Assets}}$. It is crucial that interest payments are not included since it is endogenous to the choice of debt structure. In alternative specifications, we use levels and changes in foreign currency borrowing as predictors of future performance since firms could, in principle, signal both via high foreign currency debt share or increases in it. Both specifications lend support to our predictions. Moreover, a greater increase in foreign currency debt share also predicts higher future capital expenditures. We rule out alternative explanations through several robustness checks. We also use other potential signaling variables identified in the literature as control variables, pointing to a signaling power of the foreign currency debt share on its own.

We first report the results with the levels of foreign currency debt share. We use the following specification as the baseline, restricting our sample to firms that have at least once borrowed in foreign currency:[20]

$$\frac{\text{EBIT}_{f,t+1}}{\text{Assets}_{f,t+1}} = \beta_1(\Delta)\text{foreign currency share}_{f,t} + \beta_2\frac{\text{EBIT}_{f,t}}{\text{Assets}_{f,t}} + \beta_3\text{yoy stock return}_{f,t} \\ + \beta_4\text{other firm controls}_{f,t} + \eta_{c(f),i(f),t} + \gamma_f + \epsilon_{f,t} \tag{9}$$

Across various specifications that we report in Table 3, we keep a rich set of control variables and fixed effects. These variables intend to restrict the comparison to firms that are similar in terms of observable characteristics and capture publicly available information that might be available to investors to predict these firms' earnings. We use Country×Industry×Year×Quarter interaction fixed effects to absorb variation along these dimensions and compare firms within the same country and industry in a given year and quarter.[21] In addition, we use firm fixed effects to take out average performance differences across firms. Finally, we use an extensive selection of control variables to endow investors with a rich information set. In particular, we control for year-on-year stock returns between year $t-1$ and t and the market capitalization of the firm in year t (computed using the companies' period-end stock prices) to account for any information about future performance that is already reflected in the firm's stock returns and valuations. We also include the current level of $\frac{\text{EBIT}_{f,t}}{\text{Assets}_{f,t}}$ to control for potential persistence in earnings.[22] We also control for the local currency stock

[20]We restrict our attention to such firms with "access" to foreign currency borrowing in order to rule out a potential selection mechanism that might drive both foreign currency borrowing and performance. Nonetheless, the results are similar if we also include firms that we classify as "no access" firms in the analysis.

[21]In our yearly panel, firms report at the end of their fiscal year. This results in firms reporting in different quarters. Adding the quarter interaction corrects for any potential bias arising from this inconsistency. As firms' reporting practices differ, we avoid look-ahead bias by using stock prices at actual period ends instead of the year ends.

[22]The results are quantitatively robust if we do not include current EBIT/Assets.

return-dollar β. Other financial controls include log liabilities, log capital expenditures, Altman's z-score, and the current ratio at year t. We cluster standard errors at the industry level.[23]

Previous literature has identified total debt and investment as two potential signaling variables that firms use in their corporate finance decisions (e.g. Grenadier and Malenko, 2009; Hennessy, Livdan and Miranda, 2010; Morellec and Schuerhoff, 2011). By controlling for log liabilities and log capital expenditures, we take into account the possibility that firms might also signal through these variables. Therefore, we interpret any residual predictive power of foreign currency share of debt as a signaling device on its own beyond other potential signaling devices proposed in the literature.

We report the results of various specifications in Table 3.[24] We vary the measurement of foreign currency share$_{f,t}$, use different subsamples for robustness checks, and predict future capital expenditures in addition to $\frac{\text{EBIT}}{\text{Assets}}$. In column (1), we present the baseline results. In column (2), we use hard currency share$_{f,t}$, which is constructed similarly to foreign currency share$_{f,t}$, but with only USD, EUR, CHF, GBP and JPY in the numerator. Borrowing in these currencies not only generates a currency mismatch but a substantially riskier one as these currencies tend to appreciate against EM currencies during downturns, potentially intensifying their role in signaling. In column (3), we use fc share (bank loan)$_{f,t}$, which is constructed similarly to foreign currency share$_{f,t}$ but captures only the foreign currency share of bank loans in contrast to total debt as the signaling device. In column (4), we restrict attention only to firms in non-tradable sectors.[25] Since firms in non-tradable sectors only have local currency revenues, we expect our channel to be stronger as foreign currency borrowing results in currency mismatches that are potentially easier for investors to observe. In column (5), we restrict attention only to "domestic" firms, those that do not have a foreign parent and are only domestically listed. In column (6), we further reduce the sample in (5) to only firms with a positive foreign currency debt share each year. In column (7), we use the control variables in the baseline column (1), this time predicting future log capital expenditures.

[23] Adding additional clusters along year and/or country dimensions do not substantially change the results, as we show in Table C5. However, adding these dimensions significantly reduces the number of clusters, which may not be desirable (Cameron and Miller, 2015).

[24] To give a sense of the sample coverage, over 4800 firms from 19 countries are in the identifying sample of Table 3, column (1).

[25] We follow Aguiar and Gopinath (2005) and classify industries with SIC codes 2000-3999 as tradable.

We provide further robustness checks in the appendix, varying the performance metrics and also subsamples to ensure our results are not driven by imperfections in data reporting to Capital IQ.[26]

Across many specifications in Table 3, the foreign currency share of debt positively and statistically significantly predicts one-year ahead $\frac{\text{EBIT}}{\text{Assets}}$ for negative beta firms. This holds across different specifications and sub-samples. In terms of magnitudes, controlling for all other firm-level characteristics, a ten percentage point increase in foreign currency share in year t predicts between 4 and 10 basis points higher $\frac{\text{EBIT}}{\text{Assets}}$ across different specifications, which corresponds to around 1% to 2.5% of the average value of $\frac{\text{EBIT}}{\text{Assets}}$ which is around 4 percent. Our estimates are likely to be conservative since we have endowed investors with a large information set with our firm-level controls.

Different specifications we consider rule out potential alternative explanations.

We rule out the possibility that firms self-select into foreign currency borrowing, and the characteristics that allow them to borrow in foreign currencies also help them generate higher returns. To address this concern, we restrict our sample to firms with access to FX borrowing during the whole sample or each period, as in column (6).

Across all specifications, we use Country$\times$Industry$\times$Year$\times$Quarter fixed effects, which allows us to compare firms in the same country, which operate in the same industry, and at a given year and quarter (yearly data are not reported in the same quarter across countries). This rules out potential time-varying differences across countries or industries that could drive our results, including country-level UIP deviations. Utilizing only within country-industry-year-quarter variation is conceptually closer to the key mechanism of firm-level asymmetric information highlighted in our model. Moreover, including firm fixed effects and firm controls such as current period $\frac{\text{EBIT}}{\text{Assets}}$ and year-on-year stock returns, among others, endow investors with very rich information set singling out the role of foreign currency debt share in predicting firm performance.

We also rule out the possible explanation that foreign currency share of debt positively predicts

[26] We compute percentage discrepancy between total debt reported on the main balance sheets and total outstanding debt aggregated from the security-level capital structure module of Capital IQ, and use this discrepancy measure to create Table C3. We re-run the baseline panel regressions but keep only the firm-year observations within a range of discrepancy. We show that our baseline results are robust, regardless of whether the range is set to be 25%, 10%, 5%, or 1%.

Table 3: Signaling channel of foreign-currency debt (levels): Full panel

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) domestic $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) domestic and pos. fc $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) log(capex)$_{f,t+1}$
foreign currency share$_{f,t}$ (%)	0.006***			0.010***	0.006***	0.004*	0.0004
	(0.002)			(0.003)	(0.002)	(0.002)	(0.0002)
hard currency share$_{f,t}$ (%)		0.007***					
		(0.002)					
fc share$_{f,t}$ (bank loan, %)			0.004**				
			(0.002)				
EBIT$_{f,t}$ / Asset$_{f,t}$ (%)	0.373***	0.373***	0.374***	0.350***	0.379***	0.314***	0.0203***
	(0.014)	(0.014)	(0.015)	(0.028)	(0.014)	(0.017)	(0.0018)
yoy stock return$_{f,t}$	0.007***	0.007***	0.007***	0.008***	0.007***	0.007***	0.0002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.0001)
current ratio$_{f,t}$	-0.367***	-0.367***	-0.387***	-0.242***	-0.356***	-0.309***	0.0601***
	(0.047)	(0.047)	(0.053)	(0.080)	(0.050)	(0.097)	(0.0113)
z-score$_{f,t}$	0.034	0.035	0.018	0.033	0.007	-0.070	-0.0100
	(0.047)	(0.046)	(0.048)	(0.068)	(0.043)	(0.069)	(0.0077)
log capex$_{f,t}$	-0.004	-0.003	0.016	-0.057	-0.008	-0.070	0.3756***
	(0.049)	(0.049)	(0.049)	(0.067)	(0.048)	(0.083)	(0.0153)
log total liabilities$_{f,t}$	-0.874***	-0.872***	-0.938***	-0.345	-0.891***	-1.026***	0.0960***
	(0.150)	(0.149)	(0.147)	(0.318)	(0.142)	(0.159)	(0.0352)
log market cap$_{f,t}$	0.369***	0.370***	0.387***	0.439**	0.444***	0.501***	0.3248***
	(0.101)	(0.101)	(0.099)	(0.205)	(0.107)	(0.142)	(0.0206)
rolling $\beta_{f,t}$	0.032	0.031	0.021	0.108	0.030	0.033	0.0038
	(0.029)	(0.029)	(0.026)	(0.074)	(0.028)	(0.060)	(0.0040)
Observations	48,139	48,139	46,225	15,213	44,367	22,566	47,557
R-squared	0.717	0.717	0.712	0.764	0.710	0.751	0.8994
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	47	63	59	63
No. FEs	11891	11891	11566	5282	11002	7609	11821

Note: Table 3 reports panel regressions relating foreign currency share of outstanding debt to future earnings. The dependent variable is EBIT divided by total assets in the year $t+1$, expressed as percentages. All independent variables are sampled at year t. The sample period is 2005 to 2021. Our baseline samples are firms with at least one year of positive foreign-currency borrowing in the data. We also require these firms to have a negative rolling β coefficient estimated using a regression of overlapping quarterly stock returns on local currency depreciation at a monthly frequency or a positive β insignificantly larger than zero at 5% level (Newey-West standard errors). Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Column (1) focuses on all firms in our baseline sample and our baseline foreign-currency share measure containing all currencies and all types of borrowing. In columns (2) and (3), the key independent variable is hard-currency share (share of CHF, EUR, GBP, JPY, and USD) and share of foreign-currency bank loans (term loans and credit lines), respectively. Column (4) restricts the sample to non-tradable firms (Aguiar and Gopinath, 2005). Column (5) looks at domestic firms only, defined as firms not listed abroad and those that do not have an ultimate foreign parent. Column (6) further restricts the domestic firm sample to observations with positive foreign-currency debt outstanding. In column (7), the dependent variable is log capex. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

earnings if a firm were an exporter, as exporting firms are typically more productive (see, for example, Melitz (2003)). Previous literature suggests that non-exporting firms indeed tend to borrow in foreign currencies (Ranciere, Tornell and Vamvakidis (2014), Kim, Tesar and Zhang (2015), Salomao and Varela (2022)). Since we restrict the sample to negative beta firms (firms whose cash flows move negatively with the dollar appreciation), this is unlikely to be a large concern since we would expect exporters to have a positive beta (weaker local currency increases their competitiveness in foreign markets). To further alleviate this concern, we restrict our attention to firms in non-tradable sectors in column (4), and the results go through, and the point estimate is greater.

Finally, the fact that the results go through when we measure the foreign currency share using bank loans only is reassuring since we expect information asymmetries to be present regardless of whether the lender is a bank or not. The coefficient when we use bank loans only is slightly smaller, which could be due to information asymmetries/incentives for signaling being arguably more important when it comes to bonds than bank loans.

We repeat the same exercise using year-on-year changes in foreign currency borrowing (for example, Δ foreign currency share$_{f,t-1,t}$) instead of levels and report them in Table 4. All specifications/columns are similar to those in Table 3 otherwise. The results with changes are, to a large extent, similar to those with levels. The results in the two tables combined suggest that negative beta firms perform better not only when they have a higher foreign currency debt share but also when they increase the foreign currency share of their debt more. These findings are in line with the predictions of our model.

4.2.2 Predictive relationship around large depreciation episodes

Negative beta firms take on additional FX risk to signal their earnings capabilities. This becomes especially relevant during foreign currency appreciation episodes, which typically correspond to downturns. In our model, firms that take on more FX risk through a higher share of foreign currency debt can weather these episodes better compared to firms with lower foreign currency debt: Controlling for leverage, they generate both higher earnings and higher stock returns.

In this section, we repeat the same prediction exercise, focusing on country-specific episodes of large currency depreciation, as well as global and EM-wide crisis events, including the Great

Table 4: Signaling channel of foreign-currency debt (changes): Full panel

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) domestic $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) domestic and pos. fc $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) log(capex)$_{f,t+1}$
Δ foreign currency share$_{f,t-1,t}$ (%)	0.004***			0.003	0.004**	0.003**	0.0004**
	(0.001)			(0.003)	(0.001)	(0.002)	(0.0002)
Δ hard currency share$_{f,t-1,t}$ (%)		0.005***					
		(0.002)					
Δ fc share$_{f,t-1,t}$ (bank loan, %)			0.004***				
			(0.001)				
Observations	46,894	46,894	44,173	14,872	43,185	21,938	46,326
R-squared	0.719	0.719	0.715	0.764	0.712	0.753	0.9010
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	47	63	59	63
No. FEs	11783	11783	11311	5212	10901	7505	11716

Note: Table 4 reports panel regressions relating foreign currency share of outstanding debt to future earnings. Compared to Table 3, we use yearly changes in the foreign currency share as the key predictor. The dependent variable is EBIT divided by total assets in the year $t + 1$, expressed as percentages. All independent variables are sampled at year t. The sample period is 2005 to 2021. Our baseline samples are firms with at least one year of positive foreign-currency borrowing in the data. We also require these firms to have a negative rolling β coefficient estimated using a regression of overlapping quarterly stock returns on local currency depreciation at a monthly frequency or a positive β insignificantly larger than zero at 5% level (Newey-West standard errors). Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Column (1) focuses on all firms in our baseline sample and our baseline foreign-currency share measure containing all currencies and all types of borrowing. In columns (2) and (3), the key independent variable is hard-currency share (share of CHF, EUR, GBP, JPY, and USD) and share of foreign-currency bank loans (term loans and credit lines), respectively. Column (4) restricts the sample to non-tradable firms (Aguiar and Gopinath, 2005). Column (5) looks at domestic firms only, defined as firms not listed abroad and those that do not have a foreign ultimate parent. Column (6) further restricts the domestic firm sample to observations with positive foreign-currency debt outstanding. In column (7), the dependent variable is log capex. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Financial Crisis, the COVID-19 crisis, and the 2015 emerging market currency depreciation.[27] We follow the same panel analysis approach and use the same fixed effects and control variables when possible. The strength of this specification comes from the fact that we can compare different large depreciation episodes within firms and test whether the same firm performed better in a large depreciation episode when it had a higher foreign or hard currency debt share. We restrict the sample to periods when the local currency depreciated by more than 10% year-on-year against the dollar between t and $t + 1$ and predict $\frac{\text{EBIT}}{\text{Assets}}_{f,t+1}$ using foreign currency share$_{f,t}$, hard currency share$_{f,t}$ and Δhard currency share$_{f,t-1,t}$. Given we restrict the sample to depreciation

[27] Comparing year-end numbers, the Nominal Emerging Market Economies U.S. Dollar Index (FRED) appreciated by 10.8 percent from 2014 to 2015.

episodes of the local currency against *the dollar*, we focus mostly on the results with the hard currency share on the right-hand side.

The results are again in line with our predictions, reported in Panel (a) of Appendix C, Table C6. Firms with higher foreign currency or hard currency share perform better in terms of higher earnings during large local currency depreciation episodes. This is true in the baseline sample and when we restrict the sample further to the non-tradable sectors or domestic firms (i.e., firms that do not have a foreign parent and are not listed abroad). Furthermore, having firm fixed effects also allows us to make a within-firm statement that the same firm had higher earnings across these different episodes if they had a higher foreign currency or hard currency share. In the last column, we also check whether firms perform better when they change the hard currency share more before going into one episode versus another. The coefficient goes in the predicted direction even in this very restrictive case, albeit statistically insignificant. Panel (b) of Table C6 shows that the results remain similar if we focus on systemic global or emerging market events.

4.3 Additional support: firm age and public rating

We use our empirical framework to provide two more pieces of evidence in support of the signaling channel and report the results in Table C7 in Appendix C. First, we show in Panel (a) that the predictive relationship between earnings and FC share is stronger for younger firms in a given country (reflected in the negative interaction coefficient), consistent with the intuition that younger firms suffer from a higher degree of adverse selection. Second, we follow Sufi (2007) and measure information asymmetry faced by each firm using information on credit ratings. At each year t, firms are split into those that have received a public credit rating and those that have not yet been rated.[28] We run the predictive regressions separately on each sample and report the results in Panel (b). We find that the positive predictive relationship between FC share and future earnings is driven by firms that have not yet received a public rating. For those firms that have already been rated, the point estimates of the predictive coefficient are statistically insignificant and have a smaller magnitude.

[28] We obtain credit rating history by combining information from Refinitiv and Capital IQ's own reporting. Firms are considered to have been rated if they have ever received any rating from any agency that is not a "withdrawal".

4.4 Negative versus positive beta firms

A main distinctive feature of our theory is that in the presence of asymmetric information, firms have incentives to take on currency risk to reveal their hidden quality to their investors. In our model, the use of foreign currency debt to signal depends crucially on the co-movement of cash flows with the bilateral exchange rate of the foreign currency (the dollar in our empirical setup) and the local currency. Our model predicts that firms that do worse when the dollar appreciates (i.e., negative beta firms) borrow relatively *more* in foreign currencies to signal their quality. On the contrary, firms that do better when the dollar appreciates (i.e.) borrow relatively *less* in foreign currencies to signal their quality (Proposition 3.4). The reason is that signaling in our model operates through currency mismatch. Since positive beta firms are those that are better off during episodes of dollar appreciation, taking more dollar debt would not have any signaling value. Taking more local currency debt would, however, result in currency risk in the case of positive beta firms. This prediction is unique to our theory.[29]

The empirical evidence reported in Table 5 is in line with our theoretical predictions. For positive beta firms, a greater change in the foreign currency or hard currency share predicts lower earnings ($\frac{\text{EBIT}}{\text{Assets}}$). Our empirical tests also point to a dichotomy between positive and negative beta firms, as the point estimates are of different signs across all specifications. While the results are only statistically significant when we use changes in foreign currency or hard currency share, point estimates are similar also in levels. The results also go in the same direction for predictions of future capex. However, the result for positive beta firms is statistically insignificant.

4.5 Theory and evidence on the cost of signaling

In our final exercise, we show that both our theory and data support the conceptualization of foreign-currency borrowing as a costly signaling device. We start with a simple implication of our model, that borrowing in FC is relatively more expensive for negative beta firms:

[29] It is also another differentiating factor from Salomao and Varela (2022) since in their model, foreign currency debt only adds noise to cash flows, and firms have no signaling motive. As a result, in their model, no distinction arises between positive and negative beta firms.

Table 5: Signaling channel of foreign-currency debt: The role of stock-depreciation β

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) log(capex)$_{f,t+1}$	(6) log(capex)$_{f,t+1}$
$\beta_{f,t} > 0$, significant	0.623	0.138	0.535	0.136	0.0768	0.0487
	(0.655)	(0.617)	(0.635)	(0.618)	(0.1208)	(0.0931)
foreign currency share$_{f,t}$ (%)	0.007***				0.0004	
	(0.002)				(0.0002)	
FC share × ($\beta_{f,t} > 0$, significant)	-0.013				-0.0011	
	(0.009)				(0.0022)	
Δ foreign currency share$_{f,t-1,t}$ (%)		0.004***				0.0005**
		(0.001)				(0.0002)
Δ FC share × ($\beta_{f,t} > 0$, significant)		-0.026**				-0.0035
		(0.011)				(0.0022)
hard currency share$_{f,t}$ (%)			0.007***			
			(0.002)			
hard currency share × ($\beta_{f,t} > 0$, significant)			-0.011			
			(0.010)			
Δ hard currency share$_{f,t-1,t}$ (%)				0.005***		
				(0.002)		
Δ hard currency share × ($\beta_{f,t} > 0$, significant)				-0.028***		
				(0.010)		
Observations	48,668	47,414	48,668	47,414	48,082	46,842
R-squared	0.717	0.719	0.717	0.719	0.8996	0.9012
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	63	63	63
No. FEs	12026	11917	12026	11917	11955	11849

Note: Table 5 reports panel regression output relating firms' future earnings to foreign-currency share of borrowings, separating firms with positive stock return-depreciation βs (significantly larger than zero at 5% level, Newey-West standard errors) from those with negative βs or insignificantly positive βs. The dependent variable (columns (1) to (4)) is EBIT divided by total assets in the year $t + 1$, expressed as percentages, and log capex (columns (5) to (6)). All independent variables are sampled at year t. The sample period is 2005 to 2021. In addition to foreign-currency shares, we interact (changes in) foreign-currency shares with a dummy indicating whether firm f has a positive rolling β at year t. Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Columns (1) to (4) use foreign-currency share, changes in foreign-currency share, hard-currency share (CHF, GBP, EUR JPY, USD), and changes in hard-currency share as the key predictor. Columns (5) and (6) focus on the predictive relationship between the overall foreign-currency share and log capex. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Proposition 4.1 (Credit UIP Deviations) *The UIP credit spread* $\log(1/P_{\$}(\alpha)) - \log(1/P(\alpha)) \geq \log E[\varepsilon]$ *(respectively,* $\leq \log E[\varepsilon]$*) if* $(\log\eta)_{\varepsilon,x} < 0$ *(respectively,* $(\log\eta)_{\tilde{\varepsilon},\tilde{x}}) < 0$*). Furthermore, if the conditional density,* $\eta(x|\mu,\varepsilon)$*, depends on a parameter* β *such that* $\beta < 0$ *(respectively,* > 0*) corresponds to* $(\log\eta)_{\varepsilon,x} < 0$ *(respectively,* $(\log\eta)_{\tilde{\varepsilon},\tilde{x}} < 0$*), and is real analytic in* (β,μ,ε)*, then the* *spread* $\log(1/P_{\$}(\alpha)) - \log(1/P(\alpha))$ *is monotone decreasing in* β *for* β *close to zero, for generic parameter values.*

Proposition 4.1 illustrates a simple form of UIP deviation *at the firm level*: For negative beta firms, cash flows are lower, and the default is more likely when the foreign currency appreciates. As a result, in percentage terms, foreign bondholders lose more in such states and require higher compensation for this risk ex-ante. The compensation is larger, the more sensitive firms' cash flow is to foreign-currency appreciation. This mechanism widens the spread between foreign currency and local currency borrowing rates. Importantly, as our model focuses on the cross-section of firms, this credit risk-based UIP premium is conceptually different from the country-level *risk-free* UIP deviations in emerging markets that reflect a lower cost of borrowing for foreign currencies overall.

In Table 6, we provide evidence in support of this prediction, suggesting that bond investors rationally anticipate the impact of dollar-cash flow correlation on the riskiness of the debt. For firm-year observations with new borrowing in both dollars and the local currency, We compute average interest rates and residual maturity (in years) on dollar-denominated borrowing and local currency, weighted by the size of each case of borrowing. Similar to our treatment of firm-level outcomes and controls, both variables are winsorized at 2.5% and 97.5% tails.

We then regress the contemporary interest rate difference, $R_{USD} - R_{LC}$ on the rolling stock return-depreciation β, controlling for weighted average residual maturity to account for the term premium of the dollar versus local-currency borrowing. The use of country-time fixed effects absorbs the change in the expected depreciation of currency that enters into the UIP term. Columns (1) and (2) validate the prediction of the theory that there is a negative and significant correlation between cash flow sensitivity to exchange rate fluctuations and credit UIP deviations. Saturating the regressions with the same set of firm-level controls as in previous tables and/or firm fixed effects (columns (3) to (4)) substantially reduces the sample size and statistical power, but the point estimates we get are consistently negative.

Table 6: **Costly signaling: Testing model predictions on prices**

VARIABLES	(1) USD-LC spread$_t$ (%)	(2) USD-LC spread$_t$ (%)	(3) USD-LC spread$_t$ (%)	(4) USD-LC spread$_t$ (%)
rolling $\beta_{f,t}$	-0.0834**	-0.0813**	-0.0506	-0.0441
	(0.0379)	(0.0370)	(0.0369)	(0.1056)
USD-LC residual maturity difference$_t$ (years)	0.0283	0.0247	0.0217	0.0105
	(0.0226)	(0.0233)	(0.0250)	(0.0280)
USD share$_t$ (%)		0.0034	0.0033	-0.0036
		(0.0031)	(0.0033)	(0.0067)
Observations	2,026	2,026	1,867	1,226
R-squared	0.6055	0.6059	0.6199	0.7940
Country*Industry*Year FE	✓	✓	✓	✓
Firm FE	-	-	-	✓
Firm-level controls	-	-	✓	✓
No. clusters	49	49	49	37
No. FEs	735	735	687	820

Note: Table 6 report panel regressions results on firms' relative borrowing costs in U.S. dollar versus local currency. Our theory predicts a negative correlation between firms' cash-flow sensitivity to exchange rates and the spread it pays to borrow in foreign currency over local currency. We specialize in firm-year observations with both local currency and dollar-denominated borrowing. The dependent variable, USD-LC spread, is the difference (in percentage points) between the dollar interest rate and local-currency interest rate, with the interest rates aggregated using the sizes of each case of borrowing as weights. Columns (1) to (3) report panel regression results with country-industry-year fixed effect to account for, among other things, expected local currency depreciation. Column (4) adds firm fixed effects. In each regression, we additionally control for the difference in the size-weighted average maturity of the debt issued, and in columns (3) and (4), the set of firm-level controls we employ in the baseline panel regressions (see Table 3). Both the spread and the weighted average maturity are winsorized at 2.5 and 97.5 percentile. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusion

This paper is motivated by two observations. First, corporates in emerging market economies, for which borrowing in local currency would provide greater hedging benefits, actually borrow more in foreign currency. Second, these firms tend to issue more foreign-currency debt when the local-currency-denominated cash flow is more uncertain. We develop an international corporate finance model where firms facing adverse selection choose the composition of the debt structure between the local currency and foreign currency to signal their quality to investors. The signaling game in our model has a unique separating equilibrium, in which good firms optimally expose themselves to currency risk to reveal their type. A distinct feature of our theory is that the co-movement between the firm's cash flows and the foreign currency/local currency exchange rate is key: if the firm's cash flows tend to fall when the foreign currency appreciates, higher foreign currency share of debt signals a good type, *and, crucially, vice versa.* Our model also provides a rationale for why emerging market firms forgo hedging their currency exposures arising from their foreign currency borrowing as a growing literature documents.

Evidence using panel data analysis and local currency depreciation episodes provide support for the signaling channel in our model. We also restrict our attention to cases for which we expect information asymmetries to matter more and find that the predictive power of foreign currency share of debt is indeed stronger for younger and unrated firms. Moreover, we show evidence for another distinct prediction of our model: a higher foreign currency share predicts higher earnings for firms whose cash flows co-move negatively with the foreign currency (the dollar in our empirical setup), while it predicts lower earnings for firms whose cash flows positively with the foreign currency. Finally, we show evidence in line with another prediction of our theory about firm-level credit UIP deviations, highlighting that signaling is indeed costly for firms.

Our model has important implications for assessing vulnerabilities for emerging market firms arising from currency mismatch in the corporate sector. Our findings suggest that in the presence of information asymmetries, good firms signal their quality by exposing themselves to currency risk. As a result, firms that take on this risk are actually better placed to weather foreign currency appreciation shocks. That said, large shocks could nevertheless cause distress. Therefore, our model suggests that reducing information asymmetries would be an important policy tool to mitigate corporate risk-taking in emerging market economies. However, our results also suggest that currency mismatches alone need not be a cause for concern, as previously thought. Future work can study welfare implications arising from adverse selection.

References

Acharya, Viral V and Siddharth Vij, "Regulating Carry Trades: Evidence from Foreign Currency Borrowing of Corporations in India," Working Paper, April 2022.

Aguiar, Mark, "Investment, Devaluation, and Foreign Currency Exposure: The Case of Mexico," *Journal of Development Economics*, 2005, *78* (1), 95–113.

___ **and Gita Gopinath**, "Fire-Sale FDI and Liquidity Crises," *Review of Economics and Statistics*, 2005, *87* (3), 439–452.

Alfaro, Laura, Gonzalo Asis, Anusha Chari, and Ugo Panizza, "Corporate debt, firm size and financial fragility in emerging markets," *Journal of International Economics*, 2019, *118*, 1–19.

___**, Mauricio Calani, and Liliana Varela**, "Currency Hedging: Managing Cash Flow Exposure," Working Paper 28910, National Bureau of Economic Research July 2022.

Bedendo, Mascia and Paolo Colla, "Sovereign and corporate credit risk: Evidence from the Eurozone," *Journal of Corporate Finance*, 2015, *33*, 34–52.

Bekaert, Geert, "Market Integration and Investment Barriers in Emerging Equity Markets," *The World Bank Economic Review*, 01 1995, *9* (1), 75–107.

Bevilaqua, Julia, Galina B. Hale, and Eric Tallman, "Corporate yields and sovereign yields," *Journal of International Economics*, 2020, *124*, 103304. NBER International Seminar on Macroeconomics 2019.

Bruno, Valentina and Hyun Song Shin, "Global Dollar Credit and Carry Trades: A Firm-Level Analysis," *The Review of Financial Studies*, 02 2017, *30* (3), 703–749.

Bräuning, Falk and Victoria Ivashina, "U.S. monetary policy and emerging market credit cycles," *Journal of Monetary Economics*, 2020, *112*, 57–76.

Caballero, Julián, Ugo Panizza, and Andrew Powell, "The Second Wave of Global Liquidity: Why Are Firms Acting Like Financial Intermediaries?," IDB Publications (Working Papers) 7638, Inter-American Development Bank May 2016.

Caballero, Ricardo J. and Arvind Krishnamurthy, "Excessive Dollar Debt: Financial Development and Underinsurance," *The Journal of Finance*, 2003, *58* (2), 867–893.

Cameron, A. and Douglas Miller, "A Practitioner's Guide to Cluster-Robust Inference," *Journal of Human Resources*, 2015, *50* (2), 317–372.

Caramichael, John, Gita Gopinath, and Gordon Y. Liao, "U.S. Dollar Currency Premium in Corporate Bonds," IMF Working Paper 2021/185 2021.

Cole, Harold L., James Dow, and William B. English, "Default, Settlement, and Signalling: Lending Resumption in a Reputational Model of Sovereign Debt," *International Economic Review*, 1995, *36* (2), 365–385.

Coppola, Antonio, Arvind Krishnamurthy, and Chenzi Xu, "Liquidity, Debt Denomination, and Currency Dominance," 2022.

DeMarzo, Peter M. and Darrell Duffie, "A Liquidity-Based Model of Security Design," *Econometrica*, 1999, *67*, 65–100.

di Giovanni, Julian, Şebnem Kalemli-Özcan, Mehmet Fatih Ulu, and Yusuf Soner Baskaya, "International Spillovers and Local Credit Cycles," *The Review of Economic Studies*, 10 2021, *89* (2), 733–773.

Du, Wenxin and Jesse Schreger, "Sovereign Risk, Currency Risk, and Corporate Balance Sheets," *The Review of Financial Studies*, 2022.

___, Carolin E. Pflueger, and Jesse Schreger, "Sovereign Bond Portfolios, Bond Risks and Credibility of Monetary Policy," *Journal of Finance*, 2020, *75* (6), 3097–3138.

Eckbo, Bjorn, Ronald M Giammarino, and Robert L Heinkel, "Asymmetric Information and the Medium of Exchange in Takeovers: Theory and Tests," *Review of Financial Studies*, 1990, *3* (4), 651–75.

Eren, Egemen and Semyon Malamud, "Dominant currency debt," *Journal of Financial Economics*, 2022, *144* (2), 571–589.

Franck, Murray Z. and Vidhan K. Goyal, "Testing the pecking order theory of capital structure," *Journal of Financial Economics*, 2003, *67*, 217–248.

French, Kenneth R. and Richard Roll, "Stock return variances: The arrival of information and the reaction of traders," *Journal of Financial Economics*, 1986, *17* (1), 5–26.

Gopinath, Gita and Jeremy C Stein, "Banking, Trade, and the Making of a Dominant Currency*," *The Quarterly Journal of Economics*, 10 2020, *136* (2), 783–830.

Grenadier, Steven R. and Andrey Malenko, "Real options signalling games with applications to corporate finance," *Review of Financial Studies*, 2009, *24(12)*, 3993–4036.

Gutiérrez, Bryan, Victoria Ivashina, and Juliana Salomao, "Why is Dollar Debt Cheaper? Evidence from Peru," Working Paper January 2022.

Helwege, Jean and Nellie Liang, "Is there a pecking order? Evidence from a panel of IPO firms," *Journal of Financial Economics*, 1996, *40*, 429–458.

Hennessy, Christopher A., Dmitry Livdan, and Bruno Miranda, "Repeated signalling and firm dynamics," *Review of Financial Studies*, 2010, *23(5)*, 1981–2023.

Ivashina, Victoria, Ruth Kostas, and Priscilla Zogbi, "Advent International: Kroton Investment," HBS case collection 2018.

Jeanne, Olivier, "Why Do Emerging Economies Borrow in Foreign Currency?," CEPR Discussion Papers 4030, C.E.P.R. Discussion Papers August 2003.

Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig, "Foreign Safe Asset Demand and the Dollar Exchange Rate," *Journal of Finance*, 2021, *76* (3), 1049–1089.

Kim, Minsuk, "Financial Development, Exchange Rate Fluctuations, and Debt Dollarization: A Firm-Level Evidence," IMF Working Paper 19/168 2019.

___, Rui C. Mano, and Mico Mrkaic, "Do FX Interventions Lead to Higher FX Debt? Evidence from Firm-Level Data," IMF Working Paper 20/197 2020.

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

Kohn, David, Fernando Leibovici, and Michal Szkup, "Financial frictions and export dynamics in large devaluations," *Journal of International Economics*, 2020, *122* (C).

Koijen, Ralph and Motohiro Yogo, "Exchange Rates and Asset Prices in a Global Demand System," NBER Working Paper 27342 2020.

Leary, Mark T. and Michael R. Roberts, "The pecking order, debt capacity, and information asymmetry," *Journal of Financial Economics*, 2010, *95*, 332–355.

Levin-Konigsberg, Gabriel, Hillary Stein, Vicente García Averell, and Calixto López Castañon, "Risk Management and Derivatives Losses," 2023.

Maggiori, Matteo, Brent Neiman, and Jesse Schreger, "International Currencies and Capital Allocation," *Journal of Political Economy*, 2020, *128* (6), 2019–2066.

Melitz, Marc J., "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, November 2003, *71* (6), 1695–1725.

Mendoza, Enrique G. and Vivian Z. Yue, "A General Equilibrium Model of Sovereign Default and Business Cycles*," *The Quarterly Journal of Economics*, 04 2012, *127* (2), 889–946.

Morellec, Erwan and Norman Schuerhoff, "Corporate investment and financing under asymmetric information," *Journal of Financial Economics*, 2011, *99* (2), 262–288.

Myers, Stewart C. and Nicholas S. Majluf, "Corporate financing and investment decisions when firms have information that investors do not have," *Journal of Financial Economics*, 1984, *13*, 187–221.

Niepmann, Friederike and Tim Schmidt-Eisenlohr, "Foreign Currency Loans and Credit Risk: Evidence from U.S. Banks," *Journal of International Economics*, 2021, p. 103558.

Nikolov, Boris, Lukas Schmid, and Roberto Steri, "The Sources of Financing Constraints," *Journal of Financial Economics*, 2021, *139* (2), 478–501.

Phan, Toan, "Sovereign debt signals," *Journal of International Economics*, 2017, *104*, 157–165.

Portes, Richard and Hélène Rey, "The determinants of cross-border equity flows," *Journal of International Economics*, 2005, *65* (2), 269–296.

Ranciere, Romain, Aaron Tornell, and Athanasios Vamvakidis, "Currency mismatch, systemic risk and growth in emerging Europe," *Economic Policy*, 08 2014, *25* (64), 597–658.

Salomao, Juliana and Liliana Varela, "Exchange Rate Exposure and Firm Dynamics," *The Review of Economic Studies*, 06 2022, *89* (1), 481–514.

Sandleris, Guido, "Sovereign defaults: Information, investment and credit," *Journal of International Economics*, 2008, *76* (2), 267–275.

Spence, Michael, "Job Market Signalling," *Quarterly Journal of Economics*, 1973, *87(3)*, 355–374.

Sufi, Amir, "Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans," *The Journal of Finance*, 2007, *62* (2), 629–668.

Internet Appendix

A Symmetry Between Expressions for LC and FC shares

Define $\tilde{B} = B\alpha,\ \tilde{\varepsilon} = 1/\varepsilon,\ \tilde{\alpha} = 1/\alpha$. Let also $\tilde{X} \; = \; X/\varepsilon$. Then, in these variables, we can re-define everything in foreign currency, and the joint density can be computed using the standard formula

$$\tilde{\eta}(\tilde{x}, \mu, \tilde{\varepsilon}) \;=\; \eta(\tilde{x}/\tilde{\varepsilon}, \mu, 1/\tilde{\varepsilon})\tilde{\varepsilon}^{-3}$$

where ε^{-3} is the determinant of the Jacobian of the map $(x/\varepsilon, \mu, 1/\varepsilon) \;\to\; (x, \mu, \varepsilon) \;=\; (\tilde{x}/\tilde{\varepsilon}, \mu, 1/\tilde{\varepsilon})$. The first observation is that $(\log \tilde{\eta})_{\mu x}$ has the same sign as $(\log \eta)_{\mu x}$. The second observation is that the conditions of positive association for $\tilde{\varepsilon}$ with $\tilde{x}$ and $\tilde{\mu}$ take the form

$$0 \;\leq\; (\log \tilde{\eta})_{\mu\tilde{\varepsilon}} \;=\; (\log(\eta(\tilde{x}/\tilde{\varepsilon}, \mu, 1/\tilde{\varepsilon}) - 3\log\tilde{\varepsilon}))_{\mu\tilde{\varepsilon}} \;=\; -\tilde{\varepsilon}^{-2}(\log\eta)_{\mu\varepsilon} \;-\; \tilde{x}\tilde{\varepsilon}^{-2}(\log\eta)_{\mu x}$$

whereas

$$\begin{aligned} 0 \;\leq\; (\log\tilde{\eta})_{x\varepsilon} \;&=\; (\log(\eta(\tilde{x}/\tilde{\varepsilon}, \mu, 1/\tilde{\varepsilon}) - 3\log\tilde{\varepsilon}))_{x\varepsilon} \\ =\; -\tilde{\varepsilon}^{-2}(\log\eta)_{x\varepsilon} \;-\; &\tilde{x}\tilde{\varepsilon}^{-2}(\log\eta)_{\mu x} - \tilde{x}/\tilde{\varepsilon}^{2}(\log\eta)_{xx} \;-\; \tilde{\varepsilon}^{-3}(\log\eta)_{x\varepsilon}\,. \end{aligned} \tag{10}$$

Now, total face value is $\bar{B} = B(1+\alpha\varepsilon) \;=\; \tilde{B}\tilde{\alpha}(1 + 1/(\tilde{\alpha}\tilde{\varepsilon})) \;=\; \tilde{B}\tilde{\varepsilon}^{-1}(1+\tilde{\alpha}\tilde{\varepsilon})$ equity value is

$$E[(X-\bar{B})^+] \;=\; E[(\tilde{X}/\tilde{\varepsilon} - \tilde{B}\tilde{\varepsilon}^{-1}(1+\tilde{\alpha}\tilde{\varepsilon}))^+] \;=\; E[\tilde{\varepsilon}^{-1}(\tilde{X} - \tilde{B}(1+\tilde{\alpha}\tilde{\varepsilon}))^+]\,.$$

Similarly,

$$\bar{P}(\alpha) \;=\; E[\tilde{\varepsilon}^{-1}(1+\tilde{\alpha}\tilde{\varepsilon})(1-\tilde{\Phi}(\tilde{B}(1+\tilde{\alpha}\tilde{\varepsilon})))]$$

We can define a new expectation with the measure $\tilde{\varepsilon}^{-1}/E[\tilde{\varepsilon}^{-1}]$, and all the formulas remain the same, with I replaced by $I/E[\varepsilon]$.

B Proofs

We will be extensively using the following technical lemma.

Lemma B.1

$$E[f(X)g(X)] \;\geq\; E[f(X)]\,E[g(X)]$$

for any two monotone increasing functions f, g.

The following lemma is a direct consequence of Lemma B.1.

Lemma B.2 *Suppose that we have two random variables X_1, X_2 with probability densities η_1, η_2 such that $\eta_1(x)/\eta_2(x)$ is monotone increasing in x. Then, $E[f(X_1)] \geq E[f(X_2)]$ for any monotone increasing function f.*

Proof of Proposition 3.3. At an interior optimum of

$$\max_\alpha E[\Psi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]\,,$$

we get that the first order condition defining the candidate optimum $\alpha = A(\mu)$ is given by

$$-E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))(B'(\alpha)(1+\varepsilon\alpha)+B(\alpha)\varepsilon)] \;=\; 0\,,$$

where $B(\alpha) = I/\bar{P}(\alpha)$ and where

$$\bar{P}(\alpha) \;=\; E[(1+\varepsilon\alpha)(1-\Phi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon))\,.$$

Thus, we have

$$B'(\alpha) = -I\bar{P}'(\alpha)\bar{P}(\alpha)^{-2}$$

and hence

$$\begin{aligned}
0 \;&=\; -E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))(-I\bar{P}'(\alpha)\bar{P}(\alpha)^{-2}(1+\varepsilon\alpha)+I\bar{P}(\alpha)^{-1}\varepsilon)] \\
&=\; -I\bar{P}'(\alpha)\bar{P}(\alpha)^{-2}\,\underbrace{E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))(1+\varepsilon\alpha)]}_{=\bar{P}(\alpha)} \\
&+\; I\bar{P}(\alpha)^{-1}E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))\varepsilon] \\
&=\; I\bar{P}(\alpha)^{-1}(-\bar{P}'(\alpha)+E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))\varepsilon])\,,
\end{aligned} \tag{11}$$

and the claim follows. Q.E.D.

Proof of Proposition 3.4. We have

$$\mu'(\alpha) \;=\; \frac{d}{d\alpha}F = \; F_x \bar{P}'(\alpha) \;+\; F_y\,. \tag{12}$$

By the implicit function theorem,

$$F_x \;=\; \frac{1 \;-\; I^{-1}E[((1+\varepsilon y)I/x)^2\eta((1+\varepsilon y)I/x,\;F,\;\varepsilon)]}{-E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x,\;F,\;\varepsilon)]}$$

and

$$F_y \;=\; \frac{E[\varepsilon((1-\Phi((1+\varepsilon y)I/x,\;F,\;\varepsilon)) - ((1+\varepsilon y)I/x)\varepsilon\eta((1+\varepsilon y)I/x,\;F,\;\varepsilon))]}{E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x,\;F,\;\varepsilon)]}$$

By Proposition 3.3, we have

$$\bar{P}'(\alpha) \;=\; E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu(\alpha),\varepsilon))]\,.$$

As a result, use the shorthand notation $z = B(\alpha)(1+\varepsilon(\alpha)) = (1+\varepsilon(\alpha))I/\bar{P}(\alpha)$, we have

$$\begin{aligned}
\mu'(\alpha) \;&=\; \frac{E[(1-I^{-1}z^2\eta(z))]}{-E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x,\;F,\;\varepsilon)]}E[\varepsilon(1-\Phi(z))] \\
&+\; \frac{E[\varepsilon((1-\Phi(z)-z\eta(z))]}{E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x,\;F,\;\varepsilon)]} \\
&=\; \frac{-I^{-1}E[z^2\eta(z)]\,E[\varepsilon(1-\Phi(z))] \;+\; E[\varepsilon z\eta(z)]}{-E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x,\;F,\;\varepsilon)]}\,.
\end{aligned} \tag{13}$$

Since $\Phi_\mu < 0$, the sign of $\mu'(\alpha)$ coincides with that of

$$\begin{aligned}
\psi(\alpha) \;&\equiv\; -I^{-1}E[(I/\bar{P})^2(1+\varepsilon\alpha)^2\eta((I/\bar{P})(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi((I/\bar{P})(1+\varepsilon\alpha)))] \\
&+\; E[\varepsilon(I/\bar{P})(1+\varepsilon\alpha)\eta((I/\bar{P})(1+\varepsilon\alpha))] \\
&=\; I/(\bar{P})^2\Big(-E[(1+\varepsilon\alpha)^2\eta((I/\bar{P})(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi((I/\bar{P})(1+\varepsilon\alpha)))] \\
&+\; E[\varepsilon(1+\varepsilon\alpha)\eta((I/\bar{P})(1+\varepsilon\alpha))]\bar{P}\;\Big) \\
&=\; I/(\bar{P})^2\Big(-E[(1+\varepsilon\alpha)^2\eta(\kappa(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi(\kappa(1+\varepsilon\alpha)))] \\
&+\; E[\varepsilon(1+\varepsilon\alpha)\eta(\kappa(1+\varepsilon\alpha))]E[(1+\varepsilon\alpha)(1-\Phi(\kappa(1+\varepsilon\alpha)))]\Big)
\end{aligned} \tag{14}$$

where we denote $\kappa = I/\bar{P}$. Let us change the measure to $(1+\varepsilon\alpha)(1-\Phi(\kappa(1+\varepsilon\alpha)))/E[(1+\varepsilon\alpha)(1-\Phi(\kappa(1+\varepsilon\alpha)))]$, and denote the covariances under this measure as Cov^*. Then, the sign of (14) coincides with that of

$$\mathrm{Cov}^*(\varepsilon/(1+\varepsilon\alpha),\,(1+\varepsilon\alpha)h(\kappa(1+\varepsilon\alpha)))$$

where we have defined

$$h(x,\mu,\varepsilon) \;=\; \frac{\eta(x|\mu,\varepsilon)}{1-\Phi(x|\mu,\varepsilon)}\,.$$

Thus, by Lemma B.1, the sign of $\mu'(\alpha)$ is positive (negative) if the function $(1+\varepsilon\alpha)h(\kappa(1+\varepsilon\alpha))$ is monotone increasing (decreasing) in ε. Now,

$$\frac{d}{d\varepsilon}((1+\varepsilon\alpha)h(\kappa(1+\varepsilon\alpha))) \;=\; \alpha h \;+\; \kappa\alpha(1+\varepsilon\alpha)h_x \;+\; (1+\varepsilon\alpha)h_\varepsilon\,, \tag{15}$$

and h_ε is proportional to $\frac{\eta_\varepsilon}{\eta} - \frac{\int_x^\infty \eta_\varepsilon(y)dy}{\int_x^\infty \eta(y)dy}$, and hence h_ε is positive when $\frac{\eta_\varepsilon}{\eta}$ is decreasing in x. Since η is log-concave, standard properties of log-concave densities imply that $h(x)$ is monotone increasing. Suppose that $(\log\eta)_{\varepsilon x} < 0$ (the case of $(\log\tilde{\eta})_{\tilde{\varepsilon}x} < 0$ is analogous). This is equivalent to $\frac{\eta_\varepsilon}{\eta}$ being monotone decreasing in x. Thus, $h_\varepsilon > 0$ in this case, and hence all three terms in (15) are positive, and therefore (15) is positive.

To prove the last claim (monotonicity of the equity value with respect to μ), we notice that is easier to study monotonicity with respect to α. We have

$$\frac{d}{d\alpha}E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon)] \;=\; \mu'(\alpha)\,E[\Psi_\mu((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon)]\,. \tag{16}$$

Here,

$$\Psi_\mu \;=\; \int_x^\infty (y-x)\eta_\mu(y|\mu,\varepsilon)dy$$

By assumption, η_μ/η is monotone increasing in y and hence, by Lemma B.1, we have

$$\frac{\int_x^\infty (y-x)\eta_\mu(y|\mu,\varepsilon)dy}{1-\Phi(x)} \;\geq\; \frac{\int_x^\infty (y-x)\eta(y|\mu,\varepsilon)dy}{1-\Phi(x)}\frac{\int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy}{1-\Phi(x)}$$

Since $\Phi_\mu \leq 0$, we have $\int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy = -\Phi_\mu \geq 0$. If $\mu(\alpha)$ is increasing in α, then we get the required. If $\mu(\alpha)$ is decreasing in α, then the equity value $E(\alpha) \;=\; E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon)]$ is decreasing in α and hence $E(\mu)=E(A(\mu))$ is increasing in μ.

Q.E.D.

Lemma B.3 *The following is true:*

- *If $A(\mu)$ is monotone increasing in μ and*

$$\frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}$$

is monotone increasing in ε for all $\alpha\in\mathbb{R}_+$, then $A(\mu)$ is indeed the optimum;

- *If $A(\mu)$ is monotone decreasing in μ and*

$$\frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}$$

is monotone decreasing in ε for all $\alpha\in\mathbb{R}_+$, then $A(\mu)$ is indeed the optimum.

Proof of Lemma B.3. To prove that $\alpha = A(\mu)$ is indeed the maximizer of the equity value, it would suffice to show that the derivative of the equity value is negative for $\alpha < A(\mu)$ and positive otherwise. That is, it suffices to show that

$$E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))(B'(\alpha)(1+\varepsilon\alpha)+B(\alpha)\varepsilon)] \;<\; 0 \tag{17}$$

for $\alpha < A(\mu)$ and that the sign flips for $\alpha > A(\mu)$. Equivalently, we can rewrite the optimality condition (17) for $\alpha < A(\mu)$ as

$$\frac{B'(\alpha)}{B(\alpha)} \;<\; -\frac{E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}{E[(1+\varepsilon\alpha)\,(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]},\;\alpha < A(\mu). \tag{18}$$

The proof for the case $\alpha > A(\mu)$ is analogous. Suppose first that $A(\mu)$ is monotone increasing in μ. Then, we need to show (18) for $\mu > \mu(\alpha)$. Since (18) holds with equality for $\mu = \mu(\alpha)$, it would be sufficient to show that the function $\frac{E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}{E[(1+\varepsilon\alpha)\,(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}$ is monotone decreasing in μ. Differentiating this function with respect to μ, we get that we need the inequality

$$\begin{aligned}&-E[\varepsilon\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]E[(1+\varepsilon\alpha)(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]\\&+E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]E[(1+\varepsilon\alpha)\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)] \;\le\; 0\,,\end{aligned} \tag{19}$$

which is equivalent to

$$\begin{aligned}&-E[\varepsilon\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]\\&+E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]E[\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)] \;\le\; 0\,,\end{aligned} \tag{20}$$

Changing the density to $(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))/E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]$, and denoting expectations under this density with E^*, we can rewrite the desired inequality as

$$-\mathrm{Cov}^*[\varepsilon,\frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}] \;\le\; 0\,,$$

which follows from Lemma B.1 and the assumption that $\frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}$ is monotone increasing in ε.

By contrast, if $A(\mu)$ is decreasing, then we need that $\frac{E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}{E[(1+\varepsilon\alpha)\,(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}$ be monotone increasing in μ. This is in turn equivalent to the inequality

$$-\mathrm{Cov}^*[\varepsilon, \frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}] \;\geq\; 0\,,$$

which follows from Lemma B.1 under the assumption that $\frac{\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}{1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)}$ is monotone decreasing in ε.

Q.E.D.

Lemma B.4 *We always have that*

$$\frac{\Phi_\mu(x,\mu,\varepsilon)}{1-\Phi(x,\mu,\varepsilon)}$$

is monotone decreasing in x. If $(\log\eta)_{x\varepsilon}\geq 0$ and $(\log\eta)_{\mu\varepsilon}\geq 0$, then

$$\frac{\Phi_\mu(x,\mu,\varepsilon)}{1-\Phi(x,\mu,\varepsilon)}$$

is monotone decreasing in ε and

$$\frac{\Phi_\mu(b+a\varepsilon,\mu,\varepsilon)}{1-\Phi(b+a\varepsilon,\mu,\varepsilon)}$$

is monotone decreasing in ε for any $a\geq 0$.

Proof of Lemma B.4. Since $\int_{\mathbb{R}}\eta(x|\mu,\varepsilon)dx=1$, we have $\int_{\mathbb{R}}\eta_\mu(x|\mu,\varepsilon)dx=0$, and hence

$$\frac{\Phi_\mu(x,\mu,\varepsilon)}{1-\Phi(x,\mu,\varepsilon)} \;=\; \frac{-\int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy}{\int_x^\infty \eta(y|\mu,\varepsilon)dy} \tag{21}$$

Differentiating with respect to x, we get that the required monotonicity is equivalent to

$$\frac{\eta_\mu(x|\mu,\varepsilon)}{\eta(x|\mu,\varepsilon)} \;\leq\; \frac{\int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy}{\int_x^\infty \eta(y|\mu,\varepsilon)dy}\,,$$

which follows directly from the assumed monotonicity of $\frac{\eta_\mu(x|\mu,\varepsilon)}{\eta(x|\mu,\varepsilon)}$.

Now, differentiating this quotient with respect to ε, we get that the sign of this derivative coincides with that of

$$-\int_x^\infty \eta_{\mu\varepsilon}(y|\mu,\varepsilon)dy \int_x^\infty \eta(y|\mu,\varepsilon)dy \;+\; \int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy \int_x^\infty \eta_\varepsilon(y|\mu,\varepsilon)dy\,.$$

Introducing the conditional probability measure $\mathbf{1}_{y\geq x}\eta(y|\mu,\varepsilon)/\int_x^\infty \eta(y|\mu,\varepsilon)dy$, we can rewrite the quantity of interest as

$$-E[\eta_{\mu\varepsilon}(X|\mu,\varepsilon)/\eta] \;+\; E[\eta_\varepsilon/\eta]\,E[\eta_\mu/\eta]\,.$$

Suppose first $(\log\eta)_{\varepsilon x}\geq 0$ and $(\log\eta)_{\mu\varepsilon}\geq 0$. Then,

$$\eta_{\mu\varepsilon} \;\geq\; \frac{\eta_\varepsilon\eta_\mu}{\eta}$$

and hence, by Lemma B.1,

$$E[\eta_{\mu\varepsilon}(X|\mu,\varepsilon)/\eta] \;\geq\; E[(\eta_\varepsilon/\eta)(\eta_\mu/\eta)] \;\geq\; E[\eta_\varepsilon/\eta]\,E[\eta_\mu/\eta]\,.$$

Q.E.D.

Proof of Proposition 3.6. We only consider the case of negative association between x,μ,ε. The opposite case is analogous.

Suppose that $(\log\eta)_{\varepsilon x}<0$. Let $\mu(\alpha)$ be a candidate equilibrium. By Proposition 3.4, it is monotone increasing in α, and hence $A(\mu)$ is also monotone increasing in α.

By assumption, $(\log\tilde\eta)_{\tilde x\tilde\varepsilon}\geq 0$ and $(\log\tilde\eta)_{\mu\tilde\varepsilon}\geq 0$. Therefore, Lemma B.4 implies that

$$\frac{\tilde\Phi_\mu(b+a\tilde\varepsilon,\mu,\tilde\varepsilon)}{1-\tilde\Phi(b+a\tilde\varepsilon,\mu,\tilde\varepsilon)}$$

is monotone decreasing in $\tilde\varepsilon$ for any $a\geq 0$.

Let $\tilde A(\mu)=1/A(\mu)$. Then, $\tilde A(\mu)$ is monotone decreasing in μ and the second item of Lemma B.3 implies that $\tilde A(\mu)$ is the interior optimum for firm value maximization over $\tilde\alpha=1/\alpha$. The proof is complete.

Q.E.D.

Proof of Proposition 3.7. We have

$$\begin{aligned}\frac{\partial}{\partial\varepsilon}\Psi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon) &= \frac{\partial}{\partial\varepsilon}\int_{B(\alpha)(1+\varepsilon\alpha)}^{\infty}(y-x)\eta(y|\mu,\varepsilon)dy \\ &= \int_{B(\alpha)(1+\varepsilon\alpha)}^{\infty}(y-x)\frac{\partial}{\partial\varepsilon}\eta(y|\mu,\varepsilon)dy\end{aligned} \tag{22}$$

where we have defined

$$x = B(\alpha)(1+\varepsilon\alpha)$$

By the monotone likelihood property, this beta will be positive if ε, y are positively related, and negative otherwise. Q.E.D.

Proof of Proposition 4.1. If $(\log\eta)_{x\varepsilon} < 0$, the variables are negatively associated and $E[\mathbf{1}_{(1+\alpha\varepsilon)I/\bar{P}(\alpha)<x}|\varepsilon]$ is monotone decreasing in ε, so that

$$\begin{aligned}P_{\$}(\alpha) &= E[\varepsilon E[\mathbf{1}_{(1+\alpha\varepsilon)I/\bar{P}(\alpha)<x}|\varepsilon]] \\ &\leq E[\varepsilon]E[\mathbf{1}_{(1+\alpha\varepsilon)I/\bar{P}(\alpha)<x}] = E[\varepsilon]P(\alpha)\end{aligned} \tag{23}$$

The opposite case of a negative association between $\tilde{x}$ and $\tilde{\varepsilon}$ is analogous. For the dependence on β, define $f(\beta) = P_{\$}(\alpha) - E[\varepsilon]P(\alpha)$. By real analyticity, for generic parameters, $f'(0) \neq 0$, and the inequality above implies that $f'(0) > 0$, implying the required monotonicity. Q.E.D.

C Data appendix, additional tables from empirical analysis

C.1 More details on data

Capital IQ We obtain Capital IQ data covering the firms' main financial statements and debt capital structure. Emerging market economies that have adopted a fully pegged or strongly managed exchange rate regime in our sample period (2005-2021) are dropped. These countries include China, Morocco, Kuwait, Saudi Arabia, and Romania. We drop firms in the financial sector (two-digit SIC code from 60 to 69). We also require that the firms included in our regressions have outstanding debt on their balance sheet (i.e., total debt not equal to zero).

Merge Capital IQ data with Worldscope We download, from Wharton Research Data Services (WRDS), the crosswalk between Capital IQ's unique identifier (`companyid`) to firms' International Securities Identification Number (ISIN).[30] We further use Worldscope monthly stock price dataset to link the ISIN numbers to Worldscope's unique permanent ID. After the merge, over 50% of the 2005-2021 CapitalIQ data have non-missing values on stock prices. Due to multi-listing, one `companyid` may correspond to multiple ISINs. For consistency, we use price information on local-listed stocks whenever possible by utilizing information from Worldscope's dataset on listed exchanges. For foreign-listed firms, we compute their stock return-depreciation βs by first transforming the stock prices to the local currency of their headquarters, also to ensure consistency. We make sure to avoid look-ahead bias by using the stock price recorded at the end of the companies' year-end when computing market caps and merging with Capital IQ financial data.

C.2 Additional robustness checks, tables, and figures

This section reports a set of extensive robustness checks on our empirical results in Section 4. Table C1 repeats the full-panel analysis reported in Table 3, but with firm-year observations with β insignificantly larger than zero excluded. Table C2 uses firm-level EBITDA in year $t+1$ as the dependent variable (for consistency, we accordingly control for the current level of EBITDA in the

[30] The mapping can be queried at https://wrds-www.wharton.upenn.edu/pages/get-data/compustat-capital-iq-standard-poors/capital-iq/identifiers/.

information set at year t). To alleviate the concern on potential inconsistencies between total debt reported in the main financial statements provided by Capital IQ and total debt aggregated from the capital structure module, we report in Table C3 robustness checks excluding observations with large deviations between the bottom-up figures and the main statement figures. Table C4 repeats the exercise of Table 5 investigating the different predictive relationship between positive-β and negative-β firms, but redefine the positive-β firm-year observations to include those with $\beta > 0$, but insignificantly larger than zero at 5% significance level. Table C5 explores a larger sample (all firms, including those who have never borrowed in foreign currencies) in Panel (a) and alternative clustered standard errors in Panel (b). Finally, Table C6 restricts the sample to years of major stress episodes, including the Great Financial Crisis (2007-08), EM-wide currency stress (2014-15), and the COVID-19 crisis (2019-20).

As an additional validation of our model, we also show in Figure C2 that our theoretical model can generate a monotonically increasing relationship between ex-post cash flow (shareholder value) volatility and foreign-currency share in borrowing, consistent with the aggregate pattern (Figure 1(b)). In Figure C3 we also report one set of equilibrium variables as functions of foreign-currency share generated by our model with a particular parameterization of the firm's conditional cash flow distribution.

Table C1: Signaling channel of foreign-currency debt: Full panel, negative-β sample

Panel (a): Levels of foreign-currency share

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) domestic $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) domestic and pos. fc $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) log(capex)$_{f,t+1}$
foreign currency share$_{f,t}$ (%)	0.006***			0.008**	0.006***	0.004*	0.0004*
	(0.002)			(0.003)	(0.002)	(0.003)	(0.0002)
hard currency share$_{f,t}$ (%)		0.007***					
		(0.002)					
fc share$_{f,t}$ (bank loan, %)			0.004**				
			(0.002)				
Observations	44,253	44,253	42,594	13,865	40,884	20,830	43,721
R-squared	0.720	0.720	0.716	0.771	0.713	0.756	0.8997
Firm-level controls	✓	✓	✓	✓	✓	✓	✓
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	46	63	59	63
No. FEs	11141	11141	10834	4897	10325	7134	11076

Panel (b): Changes in foreign-currency share

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) domestic and pos. fc $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) domestic and pos. fc $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) log(capex)$_{f,t+1}$
Δ foreign currency share$_{f,t-1,t}$ (%)	0.005***			0.003	0.005***	0.003*	0.0004**
	(0.001)			(0.003)	(0.001)	(0.002)	(0.0002)
Δ hard currency share$_{f,t-1,t}$ (%)		0.006***					
		(0.002)					
Δ fc share$_{f,t-1,t}$ (bank loan, %)			0.004***				
			(0.001)				
Observations	43,115	43,115	40,735	13,563	39,803	20,256	42,593
R-squared	0.722	0.722	0.718	0.771	0.715	0.759	0.9013
Firm-level controls	✓	✓	✓	✓	✓	✓	✓
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	46	63	59	63
No. FEs	11035	11035	10584	4833	10225	7034	10972

Note: Table C1 reports panel regressions relating foreign currency share of outstanding debt to future earnings. The dependent variable is EBIT divided by total assets in the year $t+1$, expressed as percentages. All independent variables are sampled at year t. The sample period is 2005 to 2021. Our baseline samples are firms with at least one year of positive foreign-currency borrowing in the data. We also require these firms to have a negative rolling β coefficient estimated using a regression of overlapping quarterly stock returns on local currency depreciation at monthly frequency. Unlike Table 3, firm-year observations with β insignificantly larger than zero are excluded. Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Panel (a) uses levels of foreign-currency shares as the key predictor, and Panel (b) explores the relationship between earnings, investment, and changes in foreign-currency shares. In each panel, Column (1) focuses on all firms in our baseline sample and our baseline foreign-currency share measure containing all currencies and all types of borrowing. In columns (2) and (3), the key independent variable is hard-currency share (share of CHF, EUR, GBP, JPY, and USD) and share of foreign-currency bank loans (term loans and credit lines), respectively. Column (4) restricts the sample to non-tradable firms (Aguiar and Gopinath, 2005). Column (5) looks at domestic firms only, defined as firms not listed abroad and those that do not have an ultimate foreign parent. Column (6) further restricts the domestic firm sample to observations with positive foreign-currency debt outstanding. In column (7), the dependent variable is log capex. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Signaling channel of foreign-currency debt (levels): Full panel, EBITDA

	(1)	(2)	(3)	(4)	(5)	(6)
				nontradable	domestic	domestic and pos. fc
VARIABLES	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBITDA_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005***			0.007**	0.005**	0.003
	(0.002)			(0.003)	(0.002)	(0.002)
hard currency share$_{f,t}$ (%)		0.006***				
		(0.002)				
fc share$_{f,t}$ (bank loan, %)			0.004**			
			(0.001)			
EBITDA/Total Assets (%)	0.381***	0.381***	0.382***	0.361***	0.383***	0.316***
	(0.013)	(0.013)	(0.015)	(0.025)	(0.014)	(0.020)
yoy stock return$_{f,t}$	0.006***	0.006***	0.006***	0.008***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
current ratio$_{f,t}$	-0.415***	-0.415***	-0.444***	-0.280***	-0.404***	-0.378***
	(0.042)	(0.042)	(0.049)	(0.074)	(0.044)	(0.109)
z-score$_{f,t}$	0.002	0.002	-0.015	-0.016	-0.016	-0.078
	(0.042)	(0.042)	(0.044)	(0.069)	(0.038)	(0.055)
log capex$_{f,t}$	0.010	0.010	0.033	-0.021	0.016	-0.059
	(0.038)	(0.038)	(0.041)	(0.069)	(0.038)	(0.079)
log total liabilities$_{f,t}$	-0.651***	-0.649***	-0.709***	-0.185	-0.661***	-0.663***
	(0.128)	(0.127)	(0.121)	(0.315)	(0.123)	(0.144)
log market cap$_{f,t}$	0.287***	0.287***	0.291***	0.329*	0.339***	0.378***
	(0.094)	(0.094)	(0.090)	(0.183)	(0.098)	(0.125)
rolling $\beta_{f,t}$	0.031	0.031	0.024	0.086	0.033	0.046
	(0.029)	(0.029)	(0.026)	(0.069)	(0.028)	(0.052)
Observations	48,091	48,091	46,180	15,199	44,329	22,549
R-squared	0.740	0.740	0.736	0.797	0.734	0.770
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	47	63	59
No. FEs	11885	11885	11560	5279	10999	7608

Note: Table C2 reports panel regressions relating foreign currency share of outstanding debt to future earnings. The dependent variable is EBITDA divided by total assets in the year $t + 1$, expressed as percentages. All independent variables are sampled at year t. The sample period is 2005 to 2021. Our baseline samples are firms with at least one year of positive foreign-currency borrowing in the data. We also require these firms to have a negative rolling β coefficient estimated using a regression of overlapping quarterly stock returns on local currency depreciation at monthly frequency. Column (1) focuses on all firms in our baseline sample and our baseline foreign-currency share measure containing all currencies and all types of borrowing. In columns (2) and (3), the key independent variable is hard-currency share (share of CHF, EUR, GBP, JPY, and USD) and share of foreign-currency bank loans (term loans and credit lines), respectively. Column (4) restricts the sample to non-tradable firms (Aguiar and Gopinath, 2005). Column (5) looks at domestic firms only, defined as firms not listed abroad, and those that do not have a foreign ultimate parent. Column (6) further restricts the domestic firm sample to observations with positive foreign-currency debt outstanding. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Consistency check: Full panel analysis, removing observations with debt structure inconsistent with aggregate figures

Panel (a): Levels of foreign-currency share

	(1)	(2)	(3)	(4)
	25%	10%	5%	1%
VARIABLES	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.006**	0.006***	0.006***	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	44,801	42,124	40,051	34,698
R-squared	0.723	0.727	0.729	0.742
Firm-level controls	✓	✓	✓	✓
Country*Industry*Year*Quarter FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
No. clusters	63	63	63	62
No. FEs	11520	11204	10919	10027

Panel (b): Changes in foreign-currency share

	(1)	(2)	(3)	(4)
	25%	10%	5%	1%
VARIABLES	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
Δ foreign currency share$_{f,t-1,t}$ (%)	0.003**	0.003**	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	43,623	41,004	38,947	33,737
R-squared	0.725	0.729	0.731	0.743
Firm-level controls	✓	✓	✓	✓
Country*Industry*Year*Quarter FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
No. clusters	63	63	63	62
No. FEs	11401	11090	10789	9893

Note: Table C3 repeats the exercise of Table 3, column (1), but restricts the sample further to firm-year observations with small deviations between total debt reported on the main balance sheets (CapitalIQ entry 4173), and total outstanding debt aggregated from the security-level capital structure module. From column (1) to column (4) in each panel, we progressively drop observations whose deviations (absolute values normalized by the bottom-up aggregates) are larger than 25%, 10%, 5%, and 1%. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Signaling channel of foreign-currency debt: The role of stock-depreciation β (alternative definition of positive-β)

VARIABLES	(1) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) log(capex)$_{f,t+1}$	(6) log(capex)$_{f,t+1}$
$\beta_{f,t} > 0$	0.256	0.221	0.282	0.217	-0.0505	-0.0516
	(0.271)	(0.266)	(0.259)	(0.265)	(0.0425)	(0.0338)
foreign currency share$_{f,t}$ (%)	0.007***				0.0003	
	(0.002)				(0.0002)	
FC share $\times$ ($\beta_{f,t} > 0$)	-0.001				-0.0001	
	(0.005)				(0.0006)	
Δ foreign currency share$_{f,t-1,t}$ (%)		0.005***				0.0005**
		(0.001)				(0.0002)
Δ FC share $\times$ ($\beta_{f,t} > 0$)		-0.011**				-0.0008
		(0.005)				(0.0007)
hard currency share$_{f,t}$ (%)			0.007***			
			(0.002)			
hard currency share $\times$ ($\beta_{f,t} > 0$)			-0.003			
			(0.006)			
Δ hard currency share$_{f,t-1,t}$ (%)				0.005***		
				(0.002)		
Δ hard currency share $\times$ ($\beta_{f,t} > 0$)				-0.008		
				(0.006)		
Observations	48,668	47,414	48,668	47,414	48,082	46,842
R-squared	0.717	0.719	0.717	0.719	0.8996	0.9012
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	63	63	63
No. FEs	12026	11917	12026	11917	11955	11849

Note: Table C4 reports panel regression output relating firms' future earnings to foreign-currency share of borrowings, separating firms with positive stock return-depreciation βs from those with negative βs. Compared to Table 5, the positive β firm-year observations include those with an estimated stock return-depreciation β larger than zero yet statistically insignificant at 5% level. The dependent variable (columns (1) to (4)) is EBIT divided by total assets in the year $t+1$, expressed as percentages, and log capex (columns (5) to (6)). All independent variables are sampled at year t. The sample period is 2005 to 2021. In addition to foreign-currency shares, we interact (changes in) foreign-currency share with a dummy indicating whether firm f has a positive rolling β at year t. Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Columns (1) to (4) use foreign-currency share, changes in foreign-currency share, hard-currency share (CHF, GBP, EUR JPY, USD) and changes in hard-currency share as the key predictor. Columns (5) and (6) focus on the predictive relationship between the overall foreign-currency share and log capex. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Panel regressions, alternative samples / clusters

Panel (a): All firms, including those that never borrow in FC

VARIABLES	(1) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(5) domestic $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(6) domestic and pos. fc $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(7) log(capex)$_{f.t+1}$
foreign currency share$_{f,t}$ (%)	0.007***			0.010***	0.006***	0.004*	0.0005**
	(0.002)			(0.003)	(0.002)	(0.002)	(0.0002)
hard currency share$_{f,t}$ (%)		0.007***					
		(0.002)					
fc share$_{f,t}$ (bank loan, %)			0.005**				
			(0.002)				
Observations	74,882	74,882	70,614	26,249	69,907	22,566	73,626
R-squared	0.706	0.706	0.703	0.737	0.700	0.751	0.8878
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	63	63	63	52	63	59	63
No. FEs	16978	16978	16320	8108	15787	7609	16822

Panel (b): Alternative clusters for standard error computation

VARIABLES	(1) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) domestic $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(6) domestic $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.006***	0.010**	0.006**	0.006***	0.010**	0.006***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Observations	48,139	15,213	44,367	48,139	15,213	44,367
R-squared	0.717	0.764	0.710	0.717	0.764	0.710
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Cluster	Industry Year	Industry Year	Industry Year	Firm Year	Firm Year	Firm Year
No. clusters	16	16	16	16	16	16
No. FEs	11891	5282	11002	11891	5282	11002

Note: Table C5, Panel (a) repeats the exercise of Table 3, Panel (a), using a larger sample than the baseline, including firms that have never borrowed in foreign currencies throughout our sample. Standard errors are clustered at the industry level. Panel (b) use the baseline sample, but computes standard errors using alternative clusters. In particular, in columns (1) to (3), standard errors are clustered at industry and year level. In columns (4) to (6), standard errors are clustered at firm and year level. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Signaling channel during major events

Panel (a): Large depreciation episodes (more than 10%)

VARIABLES	(1) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) domestic $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(5) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.007				
	(0.005)				
hard currency share$_{f,t}$ (%)		0.008*	0.015**	0.008*	
		(0.004)	(0.007)	(0.004)	
Δ hard currency share$_{f,t-1,t}$ (%)					0.003
					(0.004)
Observations	7,590	7,590	2,699	6,805	7,492
R-squared	0.780	0.780	0.825	0.785	0.781
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓
No. clusters	57	57	37	56	57
No. FEs	3490	3490	1489	3174	3465

Panel (b): GFC, EM crisis and COVID

VARIABLES	(1) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) nontradable & pos fc $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(6) nontradable & pos hc $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.008*	0.020**	0.028**			
	(0.004)	(0.009)	(0.012)			
hard currency share$_{f,t}$ (%)				0.008*	0.016	0.027*
				(0.004)	(0.010)	(0.014)
Observations	7,963	2,424	950	7,963	2,424	705
R-squared	0.801	0.860	0.881	0.801	0.860	0.886
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
No. clusters	60	42	32	60	42	30
No. FEs	4333	1609	714	4333	1609	538

Note: The dependent variable is EBIT divided by total assets in the year $t+1$, expressed as percentages. All independent variables are sampled at year t. Observations are included if the yearly currency depreciation exceeds 10 percent from year t to year $t+1$. The sample period is 2005 to 2021. Our baseline samples are firms with at least one year of positive foreign-currency borrowing in the data. We also require these firms to have a negative rolling β coefficient estimated using a regression of overlapping quarterly stock returns on local currency depreciation at a monthly frequency or a positive β insignificantly larger than zero at the 5% level. Firms' financial variables are winsorized at 2.5 and 97.5 percentile. Panel (a) reports the predictive regressions for firm-year observations characterized by episodes of large local currency depreciation against the U.S. dollar. Column (1) focuses on all firms in our baseline sample and our baseline foreign-currency share measure containing all currencies and all types of borrowing. In columns (2) to (4), the key independent variable is hard currency share (share of CHF, EUR, GBP, JPY, and USD). Column (3) restricts the sample to non-tradable firms (Aguiar and Gopinath, 2005). Column (4) looks at domestic firms only, defined as firms not listed abroad and those that do not have a foreign ultimate parent. In column (5), the key independent variable is yearly changes in the hard-currency share. Panel (b) repeats the exercise of Table 3, Panel (a). The samples are further restricted, such that the year $t+1$ reflect major stress episodes including the Great Financial Crisis (2008), EM-wide currency depreciation (2015), and the COVID-19 period (2020). Columns (1) to (3) uses the level of overall foreign-currency share in year t as the key predictor, while columns (4) to (6) use the level of hard-currency share (CHF, EUR, GBP, JPY, USD). Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C7: Testing the signaling channel: Additional support

Panel (a): Foreign-currency debt share interacted with firm age

	(1)	(2)	(3)	(4)	(5)	(6)
				nontradable	domestic	domestic and pos. fc
VARIABLES	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.010***			0.016***	0.010***	0.007*
	(0.003)			(0.005)	(0.003)	(0.004)
hard currency share$_{f,t}$ (%)		0.013***				
		(0.003)				
fc share$_{f,t}$ (bank loan, %)			0.006*			
			(0.003)			
fc share $\times$ above median age	-0.005*			-0.010**	-0.005	-0.003
	(0.003)			(0.005)	(0.003)	(0.005)
hc share $\times$ above median age		-0.009***				
		(0.003)				
fc share (bank loan) $\times$ above median age			-0.001			
			(0.003)			
Observations	46,246	46,246	44,462	14,323	42,705	21,871
R-squared	0.714	0.715	0.710	0.768	0.707	0.745
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓
No. clusters	61	61	61	45	61	58
No. FEs	11354	11354	11049	4965	10494	7328

Note: Table C7, Panel (a) reports results extending the predictive regressions (9). We augment the equation with an indicator variable of whether a firm's age is above or below their peers within the same country, and the interaction of this indicator with the firm's current foreign currency debt share. Column (1) uses the entire negative beta firms with foreign currency debt access. Column (2) uses hard currency share (share of CHF, EUR, GBP, JPY, and USD). Column (3) uses foreign currency share in bank loans. Columns (4) to (6) restrict the sample to firms in the nontradable sector, domestically-listed firms, and domestically-listed firms with foreign currency debt, respectively. Standard errors are clustered at the industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C7: Testing the signaling channel: Additional support (continued)

Panel (b): Negative beta firms with or without public credit ratings

	(1)	(2)	(3)	(4)	(5)	(6)
					nontradable	nontradable
	unrated	rated	unrated	rated	unrated	unrated
VARIABLES	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.007***	-0.004			0.010**	0.007
	(0.002)	(0.007)			(0.004)	(0.012)
hard currency share$_{f,t}$ (%)			0.008***	-0.004		
			(0.003)	(0.009)		
Observations	44,101	2,186	44,101	2,186	13,034	996
R-squared	0.713	0.869	0.713	0.869	0.763	0.883
Country*Industry*Year*Quarter FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓
No. clusters	63	33	63	33	47	20
No. FEs	11066	1083	11066	1083	4717	528

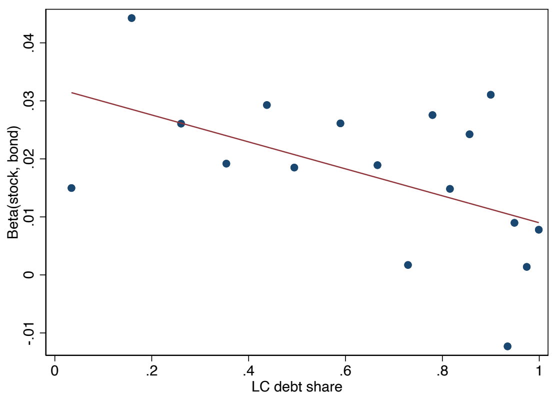
Note: Table C7, Panel (b) follows Sufi (2007) to estimate the predictive regressions separately on negative beta firms that have or have not received a public credit rating as of each year. Columns (1), (3), (5) report results for the unrated firms. Column (2), (4), (6) report results for the rated firms. Columns (3) and (4) focus on hard currency share (share of CHF, EUR, GBP, JPY, and USD). Columns (5) and (6) restrict the sample to those in the nontradable sector. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C8: Summary statistics: Negative beta regression sample

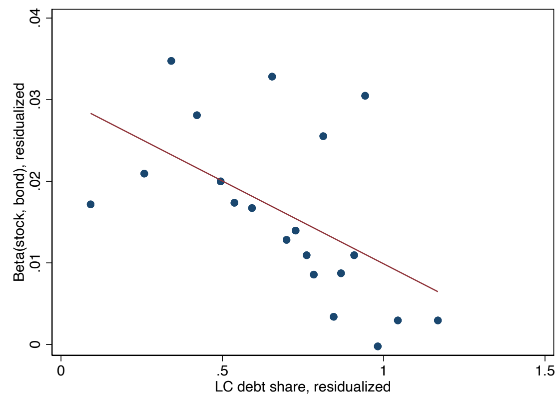
Variable	Obs	Mean	Std. Dev.	Min	Max	P50
foreign currency share (%)	48139	23.837	33.311	0	100	3.543
hard currency share (%)	48139	17.726	30.928	0	100	0
fc share (bank loan, %)	46503	25.302	35.352	0	100	1.725
EBIT / total assets (%)	48139	5.4	8.393	-32.482	27.796	5.499
log total asset (mil. USD)	48139	5.591	1.858	-2.732	12.921	5.397
log total liabilities (mil. USD)	48139	4.897	1.955	-2.355	12.109	4.702
current ratio	48139	1.667	1.307	.133	11.612	1.334
z-score	48139	2.546	2.257	-1.989	13.283	2.127
annual stock return (%)	48139	16.385	65.698	-71.429	260.082	.69
log capex (mil. USD)	48139	2.121	2.44	-13.633	10.824	2.15
log market cap (mil. USD)	48139	4.789	2.101	-3.109	13.133	4.593

Note: This table reports summary statistics for the key variables used in the predictive regression (9). The sample summarized herein corresponds to the negative beta sample used in Table 3. Foreign-currency share is the share of outstanding debt denominated in currencies other than a firm's local currency. Hard currency is defined as one of CHF, EUR, GBP, JPY, or USD. Bank loan contains two types of instruments: term loans and credit lines. The current ratio is defined as the ratio between current assets and current liabilities. The financial variables are winsorized at 2.5% and 97.5%. For each firm, monthly observations from Worldscope is used to regress overlapping quarter-over-quarter stock return on quarter-over-quarter local currency depreciation against the U.S. dollar.

Figure C1: Stock-local currency bond beta and local currency debt share: Firm-level binscatters



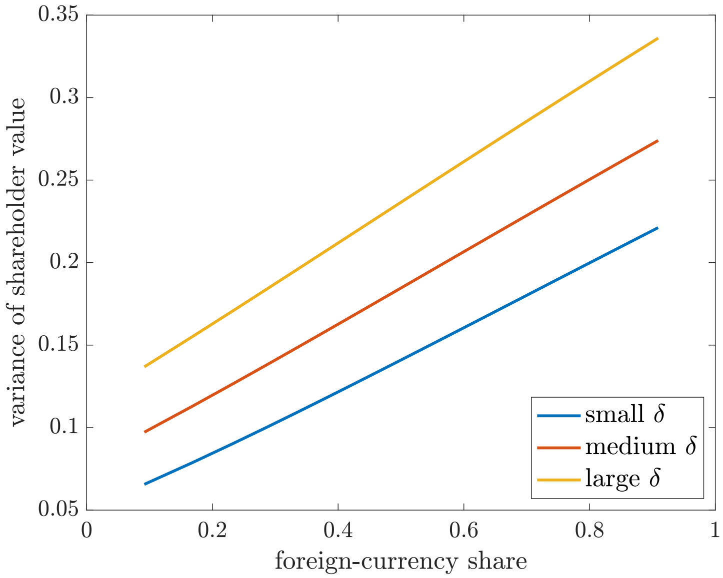
(a) Raw scatters



(b) Residualized by industry fixed effect

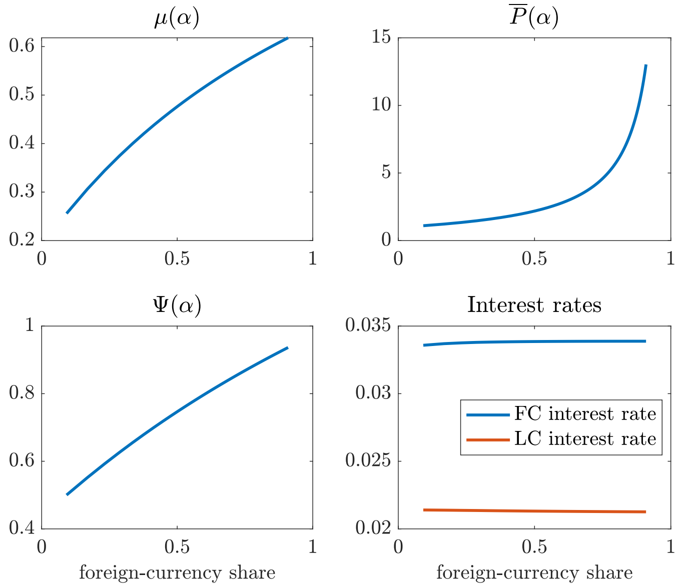
Note: Figure C1 revisits the macro correlation in Section 2 by presenting binscatter plots of firm-level stock-local currency bond beta and local currency debt share. For each firm in our Capital IQ dataset with available data, we compute firm-level stock-local currency bond $\beta(\text{Bond}, \text{Stock})$ defined in Section 2 by regressing excess stock return over three-month government bill on excess 5-year government bond return over three-month government bill. We then plot the binscatter. Local currency share for each firm is averaged over the sample period for which data is available. The red line represents fitted line from the associated firm-level regression. Panel (a) reports the raw binscatters, and Panel (b) focuses on within-industry variation by residualizing both variables against the industry fixed effect. Both binscatters are weighted by average market capitalization of each firm.

Figure C2: Model-implied relationship between foreign-currency share and stock market volatility



Note: This figure plots firms' shareholder value volatility as a function of foreign-currency share of borrowing, as implied by the theoretical model in Section 3. We focus on an increasing equilibrium and assume cash flows are conditionally log-normal with parameters $(\mu_\varepsilon, \sigma_\varepsilon)$: $\eta(x|\mu,\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma x} e^{-(\log x - f(\mu,\varepsilon))^2/(2\sigma^2)}$. with the conditional mean function given by $f(\mu,\varepsilon) = \mu - \delta\log(\varepsilon), \delta \in [1,2]$. A higher δ corresponds to a more negative $(\log\eta)_{x\varepsilon}$, and thus a larger sensitivity of cash flow to local currency depreciation. The unconditional distribution of the exchange rate is also assumed to be log-normal. Foreign-currency share is expressed as a fraction (from zero to one) by transforming the face value ratio α using the transformation $(\alpha^{-1}+1)^{-1}$. Parameter values are given by: $\varepsilon_* = e^{-1}, \varepsilon^* = e^1, \mu_\varepsilon = 0.2, \sigma_\varepsilon = 0.2, \sigma = 0.1, I = 0.5$.

Figure C3: Equilibrium model variables with a given cash flow distribution



Note: This figure plots the equilibrium variables as a function of foreign-currency share generated by the theoretical model in Section 3 for a particular set of parameter values. We focus on an increasing equilibrium and assume cash flows are conditionally log-normal with parameters $(\mu_\varepsilon, \sigma_\varepsilon)$: $\eta(x|\mu,\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma x} e^{-(\log x - f(\mu,\varepsilon))^2/(2\sigma^2)}$. with the conditional mean function given by $f(\mu,\varepsilon) = \mu - \delta \log(\varepsilon), \delta = 1.4737$. The unconditional distribution of the exchange rate is also assumed to be log-normal. Foreign-currency share is expressed as a fraction (from zero to one) by transforming the face value ratio α using the transformation $(\alpha^{-1}+1)^{-1}$. Parameter values are given by: $\varepsilon_* = e^{-1}, \varepsilon^* = e^1, \mu_\varepsilon = 0.2, \sigma_\varepsilon = 0.2, \sigma = 0.1, I = 0.5$. In the final panel, the local currency (LC) interest rate is defined as $P(\alpha)^{-1} - 1$, and the foreign currency (FC) interest rate is given by $\mathbb{E}[\varepsilon] \cdot P^{\$}(\alpha)^{-1} - 1$.

D Comparison with Salomao and Varela (2022)

The purpose of the exercise is to highlight the differences between our signaling model and the model of Salomao and Varela (2022) (henceforth SV), in which firms facing a persistent productivity process choose to borrow more in foreign currencies when current productivity is high, in order to take advantage of exogenous UIP deviations in favor of foreign-currency borrowing.

Overview We evaluate our model against SV in two ways:

- We show that our model generates the opposite patterns to SV in the dependence of foreign-currency share on model parameters associated with the volatility of exchange rate, firm productivity, and cash-flow correlation with local currency depreciation. This finding illustrates the underlying differences in the key mechanism between the two models.
- We show that in the simulated data from SV, the relationship between foreign-currency shares and future earnings is opposite to our empirical results, after controlling for current earnings.

A quick review of SV For convenience, we lay out the quantitative version of SV below.

Environment The economy is populated by a continuum of firms with idiosyncratic productivity following the $AR(1)$ process:

$$\log z' = \rho_z \log z + \sigma_z \varepsilon_z.$$

Exchange rate s (in units of LC per FC) is determined by pricing kernels of local and global investors m,m^* that depend on an exogenous state ω that follows a Cox-Ingersoll-Ross process:

$$\begin{aligned}
&s'/s = m'^*/m'. \\
&-\log m' = \tilde{\delta} + \Big(\gamma + \frac{\lambda^2}{2}\Big)\omega + \lambda\omega^{1/2}\varepsilon'_w. \\
&-\log m'^* = \Big(1 + \frac{\lambda^{*2}}{2}\Big)\omega + \lambda^*\omega^{1/2}\varepsilon'_w. \\
&\omega' = (1-\varphi)\kappa + \varphi\omega + \sigma_w\omega^{1/2}\varepsilon'_w
\end{aligned}$$

where $\{\tilde{\delta}, \gamma, \varphi, \kappa, \sigma_w, \lambda, \lambda^*\}$ are parameters.

Firm's problem Firms with idiosyncratic productivity z choose capital k', local-currency borrowing b' and foreign-currency borrowing $b^{'*}$ to maximize V, given by

$$V = \max\{V^R, V^D \equiv 0\}$$
$$V^R(\omega_{-1}, \omega, z, \nu) = \max_{\nu'}[e + \mathbb{E}_{z',\omega'}\beta V(\omega, \omega', z', \nu')]$$

where ν denotes the endogenous state $\{k, b, b^*\}$, and equity payout is given by

$$e = [Zzk^\alpha - \underbrace{i(k,k')}_{\text{investment}} - \underbrace{\psi(k,k')}_{\text{capital adj. cost}} - c_f] + [qb' + q^*sb'^* - pcI_{b'+b'^*>0}] - (b + sb^*).$$

The aggregate TFP, Z, is assumed to depend on local currency depreciation, that $Z' = (s'/s)^\zeta$. This is the β of aggregate TFP on exchange rate depreciation. A more negative ζ corresponds to a more negative correlation between local currency depreciation and cash flow.

Equilibrium Equilibrium definition can be found in SV.

Method We are especially interested in model parameters associated with second moments of exogenous processes, as these parameters govern the risk properties of a firm's cash flow and, as a result, repayment ability. To that end, we solve different versions of the SV model with the following $3^3 = 27$ combinations of model parameters (while holding other parameters unchanged as in SV):

$$\sigma_w \in \{0.098.0.196, 0.392\} \quad \sigma_z \in \{0.285, 0.57, 1.14\} \quad \zeta \in \{-0.86, -0.43, -0.215\}.$$

σ_w governs the volatility of exchange rate. σ_z denotes the volatility of idiosyncratic productivity, and ζ controls the correlation between aggregate TFP and exchange rate. The mid value in each set corresponds to the value used by SV.

After solving each iteration of the model, we simulate the model (using shock inputs provided by SV) and generate a firm-year panel with more than 600,000 firms spanning 14 years. Each set of parameter combinations generates a firm-year subpanel, which we regard as combining firms from a distinct country or industry facing potentially different exchange rates and productivity volatility, and cash flow-exchange rate correlations. We also compute the invariant distribution implied by each parameterization of the model.

Determinants of foreign-currency borrowing We first build on SV's Table 4 to understand how the choice of foreign currency borrowing is associated with productivity and model parameters, by running the following regressions:

$$Y_{f,t} = \beta \log(\text{Productivity})_{f,t} + \gamma \log(\text{Productivity})_{f,t} \times \text{Param}_f + \eta_p + \varepsilon_{f,t}$$

where $Y_{f,t}$ is either a dummy variable recording whether a firm has foreign-currency borrowing in year t, or the foreign-currency debt share. $\text{Param}_f \in \{\sigma_w, \sigma_z, \zeta\}_f$. For some specifications we include *parameter set* fixed effect to represent time-invariant heterogeneity at the "sector" level (due to differences in the set of parameters for each iteration of simulations).

Table D1 reports the regression results. Following SV we report homoskedastic standard errors. Consistent with SV, more productive firms select into borrowing in foreign currency. Our coefficient of interest is associated with the interaction term. In both panels (a) and (b), columns (1) and (2), we find that firms with higher productivity borrow even more in foreign currency if the correlation between exchange rate depreciation and aggregate productivity becomes less negative. This reflects the traditional hedging channel of debt currency choice. Firms with higher productivity borrow less in foreign currency if the exchange rate becomes more volatile (columns (3) and (4)), and if the idiosyncratic productivity process has a higher volatility (columns (5) and (6)). These results illustrate the risk management motive in the model of Salomao and Varela (2022): firms choose not to take more downside risk if the ability to repay becomes less certain.

To compare this result with our model, we solve our model numerically along a set of parameter values governing conditional volatility of cash flow, σ, as well as volatility of exchange rate σ_ε. Figure

Table D1: Decision into borrowing in foreign currency: Interaction with parameters

Panel (a): Foreign-currency dummy

	(1)	(2)	(3)	(4)	(5)	(6)
	ζ	ζ	σ_w	σ_w	σ_z	σ_z
VARIABLES	FC dummy	FC dummy	FC dummy	FC dummy	FC dummy	FC dummy
Log productivity	0.029***	0.020***	0.052***	0.047***	0.032***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log productivity interaction	0.009***	0.003**	-0.128***	-0.132***	-0.009***	-0.004***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	2,685,607	2,685,607	2,685,607	2,685,607	2,685,607	2,685,607
R-squared	0.002	0.105	0.003	0.106	0.002	0.105
Param Set FE	-	✓	-	✓	-	✓

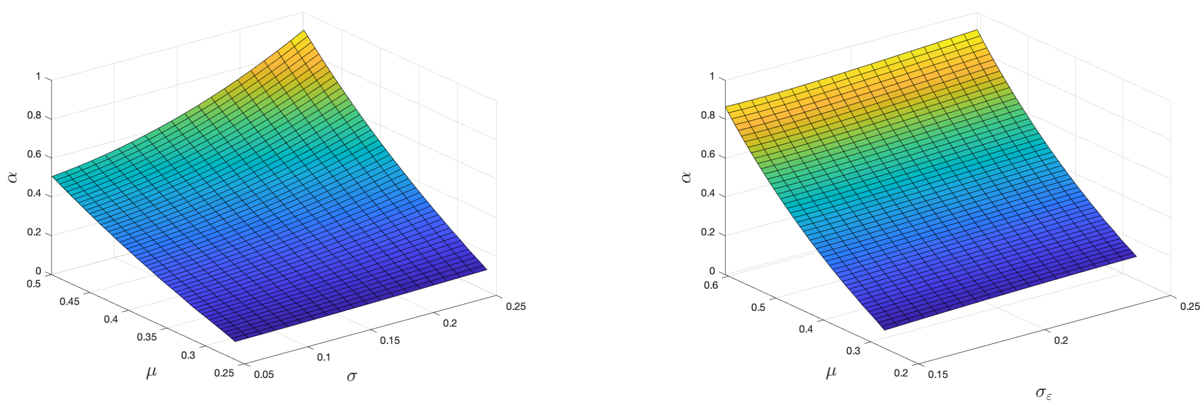
Panel (b): Foreign-currency share

	(1)	(2)	(3)	(4)	(5)	(6)
	ζ	ζ	σ_w	σ_w	σ_z	σ_z
VARIABLES	FC share	FC share	FC share	FC share	FC share	FC share
Log productivity	0.006***	0.001**	0.021***	0.020***	0.026***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Log productivity interaction	0.006***	0.002**	-0.081***	-0.090***	-0.027***	-0.025***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	2,685,607	2,685,607	2,685,607	2,685,607	2,685,607	2,685,607
R-squared	0.000	0.086	0.001	0.087	0.001	0.087
Param Set FE	-	✓	-	✓	-	✓

Note: This table reports regression results on simulated data from the Salomao and Varela (2022) quantitative model of foreign-currency borrowing. The dataset contains simulated firms under different sets of parameter values. The decision into borrowing in foreign currency is summarized by a foreign-currency dummy (Panel (a)), indicating whether a firm has foreign-currency debt in a particular year, and by the share of foreign-currency debt of the firm (Panel (b)). Guided by the model, the foreign-currency borrowing decision is regressed on the log idiosyncratic productivity of the firm, as well as log productivity interacting with one parameter whose value is allowed to change during simulations. Columns (1) and (2) reports regressions with log productivity interacted with ζ – aggregate TFP correlation with local currency depreciation. In columns (3) and (4), the parameter interacted is σ_w – volatility parameter of the exchange rate process. In columns (5) and (6), the parameter interacted is σ_z – volatility parameter of the idiosyncratic productivity process. Standard errors are homoskedastic. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D1 shows that in each case, conditional on the same firm type, optimal foreign-currency share is *increasing* in the volatility parameters. This finding, along with our numerical results in the main text on foreign-currency share and cash flow correlation with the exchange rate (see Figure 2), illustrates the underlying signaling mechanism at work in our model.

Figure D1: Foreign-currency share and volatility: Results from the signaling model



(a) σ: conditional volatility of cash flow

(b) σ_ε: volatility of exchange rate

Note: This figure reports firms' optimal foreign-currency share as a function of the hidden type, μ, and the model parameter σ (Panel (a), conditional volatility of cash flow), or σ_ε (Panel (b), volatility of exchange rate), from the numerical computation of the signaling model presented in Section 3. We focus on an increasing equilibrium and assume cash flows are conditionally log-normal with parameters $(\mu_\varepsilon, \sigma_\varepsilon)$: $\eta(x|\mu,\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma x} e^{-(\log x - f(\mu,\varepsilon))^2/(2\sigma^2)}$. with the conditional mean function given by $f(\mu,\varepsilon) = \mu - \delta \log(\varepsilon)$. The unconditional distribution of the exchange rate is also assumed to be log-normal. Foreign-currency share is expressed as a fraction (from zero to one) by transforming the face value ratio α using the transformation $(\alpha^{-1}+1)^{-1}$. Default parameter values are given by: $\varepsilon_* = e^{-1}, \varepsilon^* = e^1, \mu_\varepsilon = 0.2, , I = 0.5$. We take $\sigma_\varepsilon = 0.2$ in Panel (a), and $\sigma = 0.1$ in Panel (b).

Predictive regressions We next investigate if the data generated by SV also suggests a similar predictive relationship between foreign-currency debt share and future earnings. We run the following predictive regressions, consistent with our specification (9) in the empirical section:

$$\text{Earnings}_{f,t+1} = \delta_0 \text{Earnings}_{f,t} + \delta_1 \cdot \text{FC share}_{f,t} + \eta_f + \gamma_{p,t} + \varepsilon_{f,t}$$

where Earnings $= (s/s_{-1})^{\zeta} \cdot zk^{\alpha}$ is backed out from the production function. η_f denotes firm fixed effect. $\gamma_{p,t}$ is the parameter set×year fixed effect that resembles the country×industry×year fixed effect in our empirical setting.

Table D2 reports the results from the predictive regressions. We report standard errors clustered at the parameter set ("sector") level (homoskedastic standard errors are very similar quantitatively). The coefficients associated with foreign-currency shares are consistently negative in all four specifications, suggesting that a higher foreign-currency share predicts lower earnings going forward.

Table D2: Predictive regressions: Simulated data from Salomao and Varela (2022)

	(1)	(2)	(3)	(4)
			Positive FC	Positive FC
VARIABLES	$\text{Earning}_{f.t+1}$	$\text{Earning}_{f.t+1}$	$\text{Earning}_{f.t+1}$	$\text{Earning}_{f.t+1}$
$\text{Earning}_{f,t}$	0.658***	0.498***	0.622***	0.389***
	(0.002)	(0.002)	(0.008)	(0.010)
$\text{FC share}_{f,t}$	-0.248	-0.077	-0.688	-0.878***
	(0.191)	(0.229)	(0.441)	(0.284)
Observations	1,774,057	1,705,071	316,415	288,856
R-squared	0.542	0.598	0.546	0.677
Param Set*Year FE	✓	✓	✓	✓
Firm FE	-	✓	-	✓

Note: This table reports predictive regression results on simulated data from the Salomao and Varela (2022) quantitative model of foreign-currency borrowing. The dataset contains simulated firms under different sets of parameter values. Consistent with our main empirical exercise, we estimate the following specification:
$\text{Earnings}_{f,t+1} = \delta_0 \text{Earnings}_{f,t} + \delta_1 \cdot \text{FC share}_{f,t} + \eta_f + \gamma_{p,t} + \varepsilon_{f,t}$, where Earnings $= (s/s_{-1})^{\zeta} \cdot zk^{\alpha}$ is backed out from the production function. η_f denotes firm fixed effect. $\gamma_{p,t}$ is the parameter set×year fixed effect that resembles the country×industry×year fixed effect in our empirical setting. Standard errors are clustered at the parameter set level. *** p<0.01, ** p<0.05, * p<0.1.