Signaling with Debt Currency Choice *

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Abstract

Firms in emerging markets often expose themselves to currency risk by borrowing in foreign currencies. We present new evidence that they actually borrow more in foreign currencies when the local currency actually provides a better hedge in downturns. 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 comovement between cash flows and the exchange rate. We provide evidence consistent with the predictions of the model using a granular dataset including more than 4,800 firms in 19 emerging markets between 2005 and 2021. These findings are important for assessing and managing risks from currency mismatches on corporate balance sheets.

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

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1 Introduction

Emerging market firms frequently finance themselves with foreign currency debt. Many of these firms are neither exporters nor users of financial instruments to hedge against currency risk. Resulting currency mismatches on balance sheets exacerbate the impact of exchange rate shocks. While a large amount of literature examines how exchange rate risk contributes to financial stress, the microeconomic decisions regarding debt currency composition, as well as the distribution and pricing of foreign currency debt among firms, remain underexplored.

We present a new fact that motivates our study. Emerging market firms do not only expose themselves to currency risk, but they tend to borrow more in foreign currencies when their local currency provides a better hedge in downturns. Specifically, in countries where the co-movement of the returns on the local currency sovereign bond and the stock market is greater, the average foreign currency share of the emerging market corporates is larger.[1] This is counterintuitive as it implies that firms for which foreign currency borrowing is riskier borrow more in foreign currencies. This result persists even after accounting for deviations from uncovered interest rate parity (UIP), which typically makes foreign currency borrowing cheaper.

Motivated by this fact and guided by a large literature highlighting the importance of information asymmetries in the context of emerging markets, we propose a novel mechanism for foreign currency borrowing rooted in asymmetric information. We develop an international corporate finance model in which firms facing adverse selection choose the composition of their debt in local and foreign currency. Firms with private information about future cash flows have a choice to finance investment with debt denominated in local and foreign currency. Both the exchange rate and the cash flow are random variables. Each 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 a unique separating equilibrium exists where the share of foreign currency debt directly reveals the firm's hidden earning potential, and this relationship depends directly

[1] A more positive co-movement suggests that the real debt burdens with local currency debt are lower in bad times. Due to data limitations, we use sovereign yields as proxies for local currency corporate bond returns, which have been shown to co-move significantly in the literature. See Section 2 for details.

on the co-movement of cash flows with the exchange rate. Good firms willingly take on greater currency risk to signal their quality to investors, akin to the standard pecking order theory. This is because a default due to an adverse foreign currency shock is less likely for good firms. While the currency mismatch is presumed to raise borrowing costs due to the added default risk premium, it differentiates better firms in our context with asymmetric information. Ultimately, better firms maintain lower overall funding costs within this equilibrium as their lower default probabilities are fully revealed to investors.[2] A distinctive implication of the model is that the nature of this equilibrium hinges on the co-movement between the foreign currency/local currency exchange rate and the firm's cash flows: If the strength of the foreign currency is negatively related to the 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*.

Our model generates a cross-sectional distribution of the share and pricing of foreign currency debt among firms. In particular, it yields three key predictions which guide our empirical analysis. First, for typical emerging market firms, whose cash flows decrease when the U.S. dollar appreciates (i.e. "negative beta"[3] firms), the model makes the cross-sectional prediction that firms with a higher type – those with better earnings-generating abilities – take on a higher share of a foreign currency debt. We test this in predictive regressions of future earnings on the share of foreign currency debt and a battery of fixed effects and rich firm control variables. Our model predicts a positive relationship between the foreign currency share and future earnings for these negative beta firms. Second, for firms whose cash flows *increase* when the dollar appreciates (i.e. "positive beta" firms), our model predicts the opposite: a negative relationship between foreign currency share of debt and future earnings. Finally, for negative beta firms, costly signaling predicts that foreign currency borrowing is costlier for firms with stronger negative co-movement between cash flows and the dollar exchange rate.[4] Our empirical findings are consistent with these predictions.

[2] We show that our model's predictions do not depend on the existence of an exogenous borrowing cost advantage (UIP deviations) in foreign currency debt.

[3] We construct the "betas" of firms using rolling regressions of stock returns and the dollar exchange rate against the firms' local currency. This measurement is in line with our model as we show that the co-movement of cash flows or equity value with the dollar exchange rate has the same sign.

[4] The model would predict the opposite for positive beta firms. However, we do not have a sufficient number of observations with pricing data for positive beta firms in our dataset to test this prediction.

We construct a comprehensive firm-year-level panel dataset covering more than 4,800 firms in 19 emerging market economies between 2005 and 2021. We use the Capital IQ, S&P Global Market Intelligence database. 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. To our knowledge, no other dataset contains such detailed information for a wide range of countries. Following a thorough data cleaning procedure, 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. In addition, a subset of observations contains pricing information on the bonds and loans, which we use to construct a spread for the foreign currency and local currency debt of an individual firm.

We first focus on firms for which cash flows co-move negatively with the dollar. We call them "negative beta" firms. This is the case for a large majority of firms in our sample. Leveraging the granularity of the dataset and 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). We add a granular set of fixed effects, focusing only on firms within a given country and industry in a given time period. This allows us to rule out potential time-varying differences across countries or industries affecting the result, encompassing a wide range of explanations of foreign currency borrowing in the literature, including country-level differences in borrowing cost between currencies (UIP deviations), market liquidity and legal framework. We also include time-varying controls such as stock returns, firm characteristics, and financial health. Our results hold when we use the share of debt only in hard currencies, such as USD, EUR, CHF, JPY, and GBP. In addition, 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 provide additional results that are in alignment. In separate regressions, we show that the predictability of foreign currency share on earnings extends beyond one year. We also show that among negative beta firms, those with a greater foreign currency debt share perform better during large local currency depreciation episodes. Moreover, the predictive relationship between foreign currency debt share and future earnings is stronger for firms where one would expect information asymmetries to matter more, such as firms that have not received a public credit rating. Finally, we show that foreign currency share predicts earnings by itself, while its interaction with country-level UIP deviations is insignificant, suggesting a minor role for funding cost differential at the macro level in explaining the cross-section of foreign currency borrowing.

We perform a number of checks to rule out the influence of possible confounding factors. 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 natural hedges firms might have from exporting or time-varying export opportunities 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 or when we drop all firms that are identified as operating subsidiaries or in bankruptcy.[5] In additional robustness checks, to focus exclusively on the intensive margin, we focus only on firms in non-tradable sectors that have borrowed in foreign currencies in a given year. Finally, we show that the predictability of foreign currency share on future earnings remains robust after considering additional factors potentially contributing to foreign currency borrowing, such as a firm's marginal product of capital (MPK, Salomao and Varela (2022)), specialization of debt types, such as expected bankruptcy costs (Colla et al., 2013), and more general signaling devices identified in the literature such as leverage (Hennessy et al., 2010). In additional placebo tests, we run the same regressions for firms listed domestically in Australia and find no predictive relationship, which is suggestive that signaling with foreign currency debt is more relevant for firms in emerging markets.

[5]If a firm is an operating subsidiary, there is a potential omitted variable bias since the firm could potentially borrow from its parent using internal capital markets (Boyarchenko and Elias, 2023). Capital IQ data only provides static identification of firm parents as of the time of the data download. In order to identify the parents in a dynamic fashion, as well as deal with potential problems that might arise due to bankruptcies, we download all merger, acquisition and spin-off and bankruptcy data from S&P and dynamically construct the parent information using‘ the dates of these events. For this robustness check, we drop all firms that are not their own ultimate parent in a given year or if the ultimate parent is unidentified or the firm is in bankruptcy.

Crucially, in line with the key prediction of the signaling channel, we show a dichotomy between positive and negative beta firms as 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. 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 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 pricing of foreign currency and local currency debt 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 firm level 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 or macro-level borrowing cost advantage 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. This 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 contributes to several strands of literature, both theoretically and empirically. These include the large literature on why emerging market firms borrow in foreign currencies and have unhedged currency risk exposures, the nascent literature on the cross-sectional heterogeneity in firms' choices leading to currency mismatches, the literature on the international use of the dollar in global financial markets, and the literature on capital structure choice.

Our paper contributes to the literature on the financing choices of emerging market firms. In particular it provides an explanation for why these firms have unhedged currency exposures. 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). Yet, many emerging market 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). At the same time, 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)). Our results suggest that with adverse selection, signaling motives could explain why firms expose themselves to currency risk and why they do not generally hedge currency exposures.[6]

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 et al. (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. Lustig and Verdelhan (2007) show that UIP deviations can be large in emerging markets. For exporting firms, the literature focuses on the hedging channel by empirically documenting the complementarity between foreign sales and foreign

[6] In a related paper, Du et al. (2020) show that emerging market governments tend to borrow in currencies that appreciate in bad times rather than in local currency, which provides a hedge. This is a similar finding to ours for emerging market corporates. They argue that governments resort to foreign currency borrowing to alleviate the commitment problem of reducing the real value of 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 rooted in information asymmetries. Our paper is also related to studies of sovereign debt in the presence of information asymmetries (see, for example, Phan, 2017; Cole et al., 1995; Sandleris, 2008).

currency borrowing (Kedia and Mozumdar, 2003; Jiao and Kwon, 2022; Colacito et al., 2023; Liu, 2024). Using data from Peru, Gutierrez et al. (2023) show that investor demand for safety lowers the dollar deposit rate that banks pass through to loans, making them cheaper for borrowers. di Giovanni et al. (2021) show that UIP deviations can be a determinant of firms' FX borrowing. Taking dollar discount as given, Bruno and Shin (2017), Caballero et al. (2016), and Acharya and Vij (2022) show that the propensity to borrow in dollars increases when carry trade is more profitable.[7] 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.[8]

Our paper also contributes to the nascent literature on the cross-sectional distribution of foreign currency debt on emerging market firm balance sheets. Our paper is complementary to the paper by Salomao and Varela (2022), who 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. We model the role of asymmetric information, which generate some additional insights and can generate a cross-sectional distribution of foreign currency debt even in the absence of UIP deviations.

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 et al., 2015; Niepmann and Schmidt-Eisenlohr, 2021; Kohn et al., 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

[7] 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 et al. (2021) compare borrowing costs in the dollar and the euro with and without currency hedges. Coppola et al. (2022) argue that when asset markets are illiquid, firms denominate their debt in the currency of the most liquid public asset.

[8] Our results in Section 2 suggest that macro UIP deviations alone cannot explain the full picture of corporate risk-taking through FX borrowing. In addition, since UIP deviations are at the currency level, without firm heterogeneity, they cannot explain the cross-sectional distribution of foreign currency debt by themselves.

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 ability to generate earnings.

We also contribute to the literature on capital structure choice by analyzing the role of local currency and foreign currency debt in an international setting when firms face adverse selection.[9] 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.[10] 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 et al., 1990). Hennessy and Chemla (2022) highlight the importance of accounting for limited information confronting investors in testing the signaling theory.

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

Using aggregate cross-country data, we document a puzzling empirical relationship related to emerging market firms' funding currency choice: Firms whose local currency government debt provides a better hedging benefit do not borrow more in local currency.[11] We use the government local currency bond-stock beta computed as in Du et al. (2020, henceforth DPS) and find a negative correlation of local currency share in the aggregate corporate borrowing and the beta. This finding is similar to DPS, who focus on the currency composition of government debt.[12]

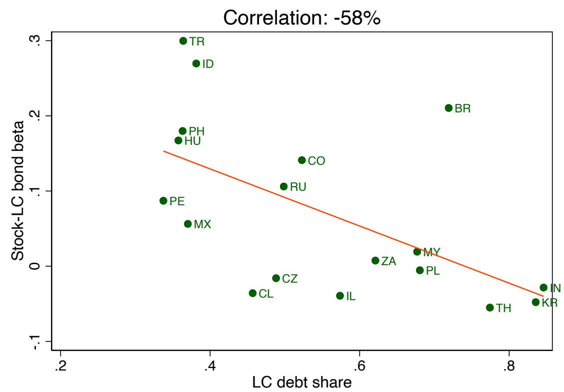
[9] Our model has three state variables: The firm's hidden type (known ex-ante), the exchange rate shock, and the cash flow shock (both realized ex-post). It turns out that the optimal signaling policy depends extremely subtly on the joint covariance structure of these three variables. Verifying the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

[10] While this logic still holds in dynamic settings with short-term private information (see Hennessy et al. (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).

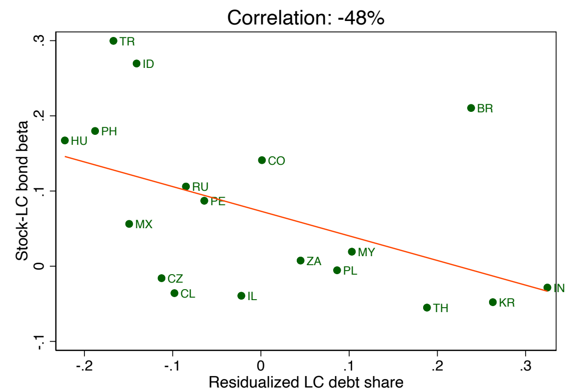
[11] In the empirical analysis, we use data for firms from 19 emerging market economies. In our aggregate analysis, we drop Argentina due to the unavailability of reliable data on LC bond spread.

[12] 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,

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



(a) Stock-local currency bond beta



(b) Residualized by 1-year UIP deviations

Note: Figure 1, Panel (a) shows the local currency stock-local currency bond beta of government debt versus corporate local currency debt share for 18 emerging market economies averaged over the sample period 2005-2021. In Panel (b), we run cross-country regressions relating the average corporate local currency debt share on the average 1-year UIP deviations calculated from exchange rate forecast data and plot the residual on the x-axis. Source for corporate local currency debt share: Capital IQ. Source for 1-year exchange rate forecast: FX4Cast. Sources for stock price, exchange rate, and bond yields: BIS, Bloomberg, and Refinitiv.

Following DPS, we define the country i's local-currency bond-stock beta as the coefficient β of the following regression:

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

In this equation, $xr^{LC}_{i,n,t}$ is the log quarterly excess return on local currency long-term bond with n periods to maturity 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. We

2012; Bedendo and Colla, 2015; Bevilaqua et al., 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.

calculate the holding period return as follows:

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

where we use the approximation $y^{LC}_{i,n-1,t+1} \approx y^{LC}_{i,n,t+1}$ for sufficiently large n, following DPS.

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 as $r^m_{i,t+1}$, 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 higher-beta local currency bonds are a better hedging instrument.

Panel (a) of Figure 1 compares local currency bond-stock beta and the average local currency share in total corporate debt (from Capital IQ) calculated using the sample 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 borrow relatively less in local currency-denominated debt, forgoing the hedging benefits of local currency. The correlation barely changes if we take into cross-country funding cost differences and residualized corporate local currency debt share using 1-year UIP deviations constructed from exchange rate forecasts (Panel (b)). 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.[13]

[13] Figure C1 in Appendix D shows that this relationship also holds if we use firm-level data to calculate

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 provides a rationale for why emerging market firms do not typically hedge their currency mismatches and may want to take on even more, as uncovered in Section 2.

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. We will also refer to α using the term "foreign currency share", as the share of foreign currency in total debt is a monotonic transformation of α. Similarly, P and $P_\$$ denote

$\beta(govt\ bond_i, stock_{j(i)})$ instead for each firm j in country i. In particular, Figure C1 plots the market-cap weighted binscatters and finds a similar negative correlation between firm-level stock-bond beta and local currency share.

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 $1/P_{\$}$ 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 impose 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.

Assumption 1 puts mild restrictions on the conditional distribution of firm cash flows and no restriction on the distribution of exchange rates. 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.[14]

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

[14] We believe that currency choice is an important signaling mechanism in the context of emerging markets in which high FX volatility could result in non-trivial exchange rate risk. However, in reality, it is possible that firms might be simultaneously signaling through other means, such as leverage. We believe a theoretical analysis of multi-dimensional signaling could be a fruitful area of future research. That said, we account for other possible mechanisms through which firms might be signaling (e.g. leverage) in the empirical section.

Lemma C.2 in the Appendix. All proofs are relegated to Appendix C. 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, fully rational and discount the future at zero rate. Under this assumption, the bond price schedules are given by

$$P(\alpha) \;=\; E[(1 - \Phi(Z(\alpha, \varepsilon), \mu, \varepsilon))|\alpha], \;\; P_\$(\alpha) \;=\; E[\varepsilon(1 - \Phi(Z(\alpha, \varepsilon), \mu, \varepsilon))|\alpha] \tag{3}$$

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

$$Z(\alpha, \varepsilon) \;\equiv\; B(\alpha) + \varepsilon B_\$(\alpha) \;=\; (1 + \alpha\varepsilon)B(\alpha) \;=\; (1 + \alpha\varepsilon)I/\bar{P}(\alpha)\,, \tag{4}$$

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 the mechanism we proposed does not rely on country-level UIP deviations. We also note that, conditional on α, shareholders' equity value is given by $E[\Psi(Z(\alpha, \varepsilon), \mu, \varepsilon)]$.

3.2 Equilibrium definition and symmetry between local and foreign currency

We focus our analysis on fully revealing, separating equilibria.[15] 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

[15] 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.

firms that can raise enough funds to finance I. To allow for rationing, we study monotone threshold rationing equilibria in which all firms of type μ above an equilibrium threshold μ_* get financing. In Appendix A.1, we formally define the separating monotone equilibrium.[16]

In our model, there is complete symmetry between the foreign currency and local currency. 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 cash flow 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 the pricing functions as

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

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 the default threshold given by

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

In particular, $\tilde{P}(\tilde{\alpha}) = \tilde{\alpha}\bar{P}(\tilde{\alpha}^{-1})$. Furthermore, the budget constraint of the firms is expressed as

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

[16]We only consider equilibria in which all pricing functions are continuously differentiable with respect to α. The equilibrium we focus on by nature rules out firms with low types "gamble for survival" through excessive leverage in foreign currency, a pooled equilibrium.

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. We provide more details on the symmetry in Appendix A.2.

3.3 Characterizing the equilibrium

To proceed, 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 (12) immediately implies that the aggregate debt pricing function satisfies

$$\bar{P}(\alpha) \;=\; E[(1+\varepsilon\alpha)(1-\Phi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon))\,. \tag{5}$$

Define $F(x,y)$ implicitly to be the unique[17] solution to

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

Then, (5) implies that in a separating equilibrium, the mapping between the foreign currency debt ratio and the hidden type of firms $\mu(\alpha)$ satisfies $\mu(\alpha) \;=\; F(\bar{P}(\alpha),\,\alpha)\,.$

To find the equilibrium debt price, we use the first order conditions for the firm in (10) : 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 (5), Proposition 3.1 characterizes the equilibrium price of debt.

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

Proposition 3.1 (Equilibrium debt pricing) *In any candidate equilibrium, the price $\bar{P}(\alpha)$ satisfies the ordinary differential equation*

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

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 (15). 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.[18]

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 3.2 (Signaling by taking on currency mismatches) *The following is true.*

- *if $(\log\tilde{\eta})_{\tilde{\varepsilon}\tilde{x}} < 0$, then any candidate equilibrium firm quality $\mu(\alpha)$ from Proposition 3.1 is monotone decreasing in α, the foreign-currency share;*

- *if $(\log\eta)_{\varepsilon x} < 0$, then any candidate equilibrium firm quality $\mu(\alpha)$ from Proposition 3.1 is monotone increasing in α, the foreign-currency share.*

Furthermore, in any equilibrium, firm equity value

$$E(\mu) \;\equiv\; E[\Psi((1+A(\mu)\varepsilon)I/\bar{P}(A(\mu)),\mu,\varepsilon)] \tag{7}$$

is monotone increasing in firm quality μ.

[18] Our model can naturally accommodate exogenous UIP deviations by adding a wedge to $P(\alpha)$. With appropriate adjustment to the rationing thresholds, the borrowing cost function $\overline{P}(\alpha)$ nevertheless still satisfies (15), with a slightly different F function. We outline the argument in Appendix B. As a result, our mechanism is entirely independent of whether there is an aggregate borrowing cost advantage in foreign currency.

The conditions of Proposition 3.2 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 $\text{Cov}(x, \varepsilon)$. 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 3.2, 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.[19]

Figure 2 illustrates the equilibrium relationship between the fraction of foreign currency and both the hidden types of firms and firms' cash flow sensitivity to the exchange rate. Lemma A.2 in Appendix A.1 outlines the procedure used to construct the numerical solution. 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.[20] 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 assumption, firms with a sufficiently high type borrow even more in foreign currency even as their cash flow becomes more sensitive to local currency depreciation.[21]

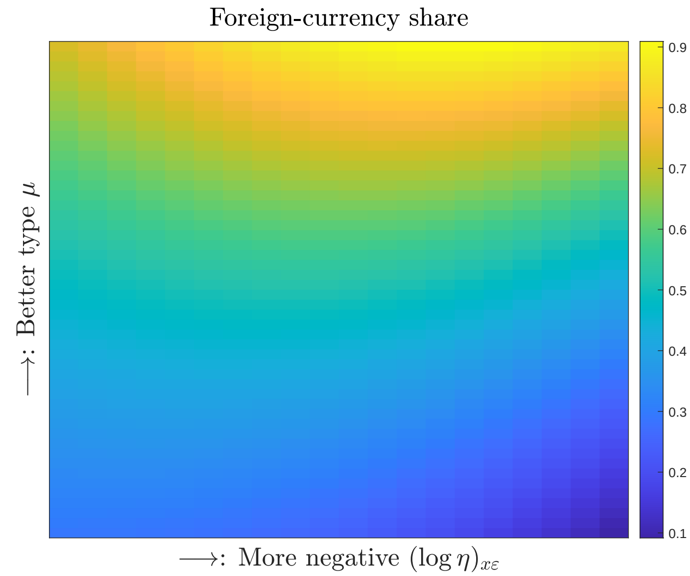
To complete the analysis, we need to verify the second-order conditions of the firm. We impose mild restrictions to ensure that the candidate optimum satisfying the first-order conditions is indeed

[19]The sufficient conditions in Proposition 3.2 only impose restrictions on the *partial* derivative of conditional cash flow distribution with respect to the exogenous shocks. As a result, lenders do not need to observe μ before making inferences on the correlations. As shown subsequently in Proposition 3.4, in equilibrium, the sign of this partial derivative is consistent with that of the ex-post correlation of firm profits with respect to the exchange rate.

[20]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 $(\log \eta)_{x\varepsilon} = x^{-1} f_\varepsilon(\mu, \varepsilon)/\sigma^2 = -(\varepsilon x)^{-1}\delta/\sigma^2$.

[21]Appendix Figure C4 plots the equilibrium quantities as functions of foreign currency share with the parameter values set within the range of values plotted in Figure 2.

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: $\varepsilon_* = e^{-1}, \varepsilon^* = e^1, \mu_\varepsilon = 0.2, \sigma_\varepsilon = 0.2, \sigma = 0.1, I = 0.5$.

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 3.3 (Equilibrium verification) *The following is true.*

- *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 3.4 (Sign equivalence between cash flow and stock beta to exchange rate) *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 $\log \tilde{\eta}_{\tilde{x}\tilde{\varepsilon}} > 0$.

Our model implies the following testable hypotheses based on Assumption 1, Proposition 3.2 and 3.4: For firms whose stock price comoves negatively with the strength of local currency, a firm with a higher foreign currency debt share is of a higher type and will generate higher cash flows going forward. The reverse is true for firms with a positive stock return beta to local currency exchange rate depreciation.

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 earnings ability to investors. Crucially, a 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, making the foreign currency debt more expensive for a given firm. Our model generates prediction on the funding cost differences at the firm level, which are conceptually different and independent of any country-level macro

UIP deviations. Using the available information on the prices of firms' debt within our dataset, we provide evidence that aligns with the model prediction. While alternative explanations can rationalize some individual results, we are unable to come up with a different 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×Industry×Year and Firm) and firm-year 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 unrated firms for which information frictions arguably matter more. In addition, we show that in line with the distinct 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 borrowing costs in local and foreign currency at the firm level is consistent with our theoretical prediction. Finally, we discuss our mechanism in relation to other alternative explanations and provide a number of robustness checks.

4.1 Data and summary statistics

We obtain firm-level balance sheet information directly 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.[22]

Before the analysis, we obtain a clean dataset by removing duplicated entries and restricting our sample to periods where the debt structure data is reported more extensively. As a result, we focus on non-financial firms from 19 major emerging market economies with flexible exchange rate regimes using yearly data between 2005 and 2021.[23] In the debt structure module, a credit line may appear multiple times each year as Capital IQ reports both the amount outstanding and the maximum amount to be drawn. When calculating foreign currency debt share, we make sure to remove the items associated with the maximum amount of the credit lines to avoid double counting. While the primary market data is not available, in later analysis, we identify new issuance of debt as the first time the debt instrument appears in the raw data, a procedure demonstrated to be reliable by Boyarchenko and Elias (2023).

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, $foreign\ currency\ share_{f,t}$ expressed in percentage terms, 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, EUR, CHF, JPY, and GBP).

Our model establishes a strong link between the cash flow sensitivity of firms to exchange rate

[22] Cross-checking with other data sources, we find that the aggregate debt statistics in our dataset broadly match them (see Table C1). To the best of our knowledge, no other data source provides such detailed information on foreign currency borrowing for a comprehensive set of emerging market economies. Kim (2019), Kim et al. (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, while Choi et al. (2018) study the dispersion of corporate debt maturities using Capital IQ debt structure data.

[23] 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. We drop firms in the public sector and financial firms, except those in the real estate sector.

shocks and firms' foreign-currency borrowing. Proposition 3.4 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 firm 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.[24] 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.

We construct our predictive regressions using a large set of firm-level financial variables. Guided by our theory, we focus on earnings before interest and taxes (EBIT), normalized by total assets as the outcome variable of interest. In our baseline specification, 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. According to Panel (a), the average foreign-currency share of total debt in our baseline regression sample is 23.7%, 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

[24] 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 the sample before the first 48-month window, we impute the β using the estimates from the first 48-month window if possible. The average window size is 102 months.

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 (including those with a statistically insignificantly positive 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.

4.2 Evidence on negative beta firms

In this section, we focus on negative beta firms as they comprise a significant share of our dataset.[25] 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 predictions, first using the panel structure and then restricting the sample to only episodes of large local currency depreciation.

4.2.1 Panel data analysis

We use our dataset's panel structure and test 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. We

[25] 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 C9). The results are very similar.

Table 1: Summary statistics

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

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
foreign currency share (%)	50821	23.733	33.381	0	100	3.085
hard currency share (%)	50821	17.681	30.925	0	100	0
EBIT / total assets (%)	50821	5.439	8.232	-28.865	27.132	5.481
log total asset (mil. USD)	50821	5.589	1.835	-3.857	12.921	5.413
log total liabilities (mil. USD)	50821	4.885	1.936	-2.355	12.049	4.72
current ratio	50821	1.707	1.353	.15	10.712	1.354
z-score	50821	2.553	2.28	-1.944	13.116	2.122
annual stock return (%)	50821	16.315	65.342	-71.624	259.504	.84
log capex (mil. USD)	50821	2.036	2.464	-13.633	10.824	2.082
log market cap (mil. USD)	50821	4.802	2.092	-3.109	13.133	4.622

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

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
negative betas	46898	-1.788	1.901	-148.824	0	-1.415
positive betas	4089	.806	1.947	0	42.46	.421
positive betas, insignificantly > 0	3570	.67	1.642	0	36.912	.352

Note: This table reports summary statistics for the key variables used in the predictive regressions (8). 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 one of CHF, EUR, GBP, JPY, or USD. 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.

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

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

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

	zero fc share		**positive fc share**		**mean diff.**
	mean	sd	mean	sd	t
EBIT / total assets (%)	5.15	(8.73)	5.66	(7.81)	6.99
log total asset (mil. USD)	5.04	(1.63)	6.02	(1.87)	62.33
log total liabilities (mil. USD)	4.27	(1.74)	5.37	(1.95)	65.92
current ratio	1.83	(1.55)	1.61	(1.18)	-18.07
z-score	2.77	(2.50)	2.39	(2.08)	-18.66
annual stock return (%)	17.39	(67.30)	15.48	(63.74)	-3.27
log market cap (mil. USD)	4.30	(1.93)	5.20	(2.12)	49.65
log capex (mil. USD)	1.35	(2.32)	2.57	(2.44)	57.26
β (negative)	-1.89	(2.27)	-1.71	(1.53)	10.30
β (positive)	0.86	(2.17)	0.77	(1.75)	-1.45
β (positive, insignificantly > 0)	0.67	(1.43)	0.67	(1.80)	0.09
Observations	22629		28358		50987

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

specification as the baseline, restricting our sample to firms that have at least once borrowed in foreign currency:[26]

$$\frac{\text{EBIT}_{f,t+1}}{\text{Assets}_{f,t+1}} = \beta_1(\Delta)\text{foreign currency share}_{f,t} + \beta_2\frac{\text{EBIT}_{f,t}}{\text{Assets}_{f,t}} + \beta_3\text{yoy stock return}_{f,t} + \beta_4\text{other firm controls}_{f,t} + \eta_{c(f),i(f),t} + \gamma_f + \epsilon_{f,t} \tag{8}$$

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

[26] 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.

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 (%)	5.51	(8.10)	4.56	(9.56)	4.34	(9.73)
log total asset (mil. USD)	5.63	(1.83)	5.08	(1.85)	5.02	(1.81)
log total liabilities (mil. USD)	4.93	(1.93)	4.31	(1.93)	4.27	(1.89)
current ratio	1.70	(1.36)	1.79	(1.38)	1.78	(1.38)
z-score	2.54	(2.26)	2.78	(2.47)	2.72	(2.48)
annual stock return (%)	15.99	(65.06)	20.15	(68.47)	19.18	(67.76)
log market cap (mil. USD)	4.82	(2.09)	4.53	(2.05)	4.45	(2.01)
log capex (mil. USD)	2.07	(2.45)	1.55	(2.59)	1.46	(2.57)
foreign currency share (%)	23.32	(33.04)	27.40	(36.21)	26.49	(35.87)
Observations	46898		4089		3570	

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%.

investors to predict these firms' earnings. We use Country×Industry×Year interaction fixed effects to absorb variation along these dimensions and compare firms within the same country and industry in a given year.[27] We take the two-digit SIC codes to define an industry. 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.[28]

[27] In our yearly panel, firms report at the end of their fiscal year. This results in firms reporting in different quarters. We avoid look-ahead bias by using stock prices at the actual period ends for each firm instead of the year ends.

[28] Our results are very similar if we exclude market cap from the set of controls.

We also include the current level of $\frac{\text{EBIT}_{f,t}}{\text{Assets}_{f,t}}$ to control for potential persistence in earnings. We also control for the level of local currency stock return-dollar rolling β.[29] 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.[30]

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 et al., 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.[31]

We report the results of various specifications in Table 3.[32] To preserve space, we highlight the coefficients associated with the foreign currency debt share and relegate detail on firm-level control variables to Table C2 in Appendix D. We vary the measurement of foreign currency share$_{f,t}$, use different subsamples for robustness checks. In column (1), we present the baseline results. From column (2) onwards, we restrict attention only to firms in non-tradable sectors, which do not possess natural hedges nor face time-varying export opportunities.[33] 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 (3), we further reduce the sample in (2) to only firms with a positive foreign currency debt share each year. In column (4), we restrict attention only to "domestic" firms, those that do not have a foreign parent and are only domestically listed. In column (5), we use hard currency share$_{f,t}$, which is constructed similarly to foreign currency share$_{f,t}$, but with only USD, EUR, CHF, GBP

[29] We compute the rolling β not winsorizing the stock return. Our results are robust to winsorizing the estimated rolling β's at 5% level, like other controls.

[30] Adding additional clusters along year and/or country dimensions do not substantially change the results, as we show in Panel (e) of Table C9. However, adding these dimensions significantly reduces the number of clusters, which may not be desirable (Cameron and Miller, 2015).

[31] Our theory-consistent empirical approach shares a similar spirit with early work testing the signaling channel. Taking the first difference of Equation (8), we arrive at a specification that generalizes Eckbo (1986, Eq. 4), who regresses changes in firm earnings on changes in market earnings and debt issuance and interprets the results as indicating abnormal returns from debt offerings. In our specification, the fixed effects absorb the impact of market return, and the autoregressive structure accounts for predictability based on current earnings.

[32] Over 4800 firms from 19 countries are in the identifying sample of Table 3, column (1).

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

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. 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.[34]

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 5 and 10 basis points higher $\frac{\text{EBIT}}{\text{Assets}}$ across different specifications, which corresponds to around 1.25% to 2.5% of the average value of $\frac{\text{EBIT}}{\text{Assets}}$ (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.[35]

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 (3), and control for a number of factors driving self-selection, such as firm sizes.

Across all specifications, we use Country×Industry×Year fixed effects, which allows us to compare firms in the same country, which operate in the same industry, and at a given year. 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 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

[34] 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%, or 5%.

[35] We include firm fixed effect in dynamic panels of firms. We perform bias correction à la Dhaene and Jochmans (2015) and show in Figure C3 in the Appendix that the induced Nickell bias is small and often leads to an attenuation of the linkage between foreign currency debt share and future earnings.

Table 3: Signaling channel of foreign-currency debt: Baseline predictive regressions

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) positive FC nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.009**	0.009**	0.009***			0.005**
	(0.002)	(0.003)	(0.004)	(0.003)			(0.002)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.003)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.006*	
						(0.003)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.016**
							(0.007)
$\beta_{f,t} > 0$, significant							0.724
							(0.581)
Observations	50,224	17,502	9,007	17,254	17,502	17,140	50,821
R-squared	0.709	0.731	0.768	0.730	0.732	0.733	0.709
Firm-level Controls	✓	✓	✓	✓	✓	✓	✓
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	57	37	33	37	37	37	57
No. FEs	10670	4810	3350	4744	4810	4771	10801

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) includes firms in both tradable and nontradable sectors defined by Aguiar and Gopinath (2005). Column (2) focuses on nontradable sectors. Column (3) restricts the sample to firm-year observations with non-zero foreign currency borrowing. Column (4) excludes firms listed overseas. In columns (5) and (6), the variable of interest is the share of hard currency debt and yearly changes in foreign currency debt share. In column (7), we introduce firm-year observations with a statistically significantly positive β and interact with a dummy indicating this positive β with foreign currency debt share. A rich set of firm-level control variables is included in the estimation but not reported. Their associated coefficients can be found in the full table (Table C2). Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

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 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 et al. (2014), Kim et al. (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 from columns (2)-(6), and the results not only go through, but the point estimate is greater.

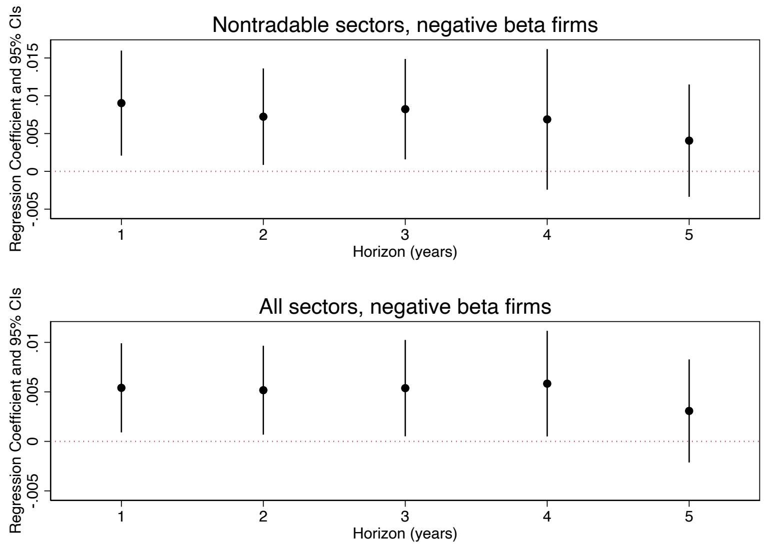
We repeat the same exercise using year-on-year changes in foreign currency borrowing (for example, Δ foreign currency share$_{f,t-1,t}$) instead of levels and report the result in column (6). The results in the two tables combined suggest that negative beta firms perform better not only when they have a higher foreign currency debt share but also when they increase the foreign currency share of their debt more. These findings further support the predictions of our model.

The predictive relationship between foreign currency share and future earnings persists for more than one year. In Figure 3, we report the estimated coefficients of foreign currency share, along with a 95% confidence band, in predictive regressions with earnings one to five years ahead as the dependent variable. In both the non-tradable sector sample and the all-firm sample, the coefficients remain positive and statistically significant after 3 years.

4.3 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 earnings abilities 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 3.2). 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

Figure 3: Predictive regressions at longer horizons



Note: Figure 3 plots the coefficients associated with foreign currency debt share in 8 with the predictive horizon extending from 1 year to 2, 3, 4, and 5 years forward. The top panel focuses on firms in the nontradable sectors (column (2) in Table 3), and the bottom panel focuses on firms in all sectors (column (1) in Table 3). 95% error bands denote standard errors clustered at the industry level.

more local currency debt would, however, result in currency risk in the case of positive beta firms. This prediction is unique to our theory.[36]

The empirical evidence reported in Column (7) of Table 3 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 ($\frac{\text{EBIT}}{\text{Assets}}$). Hence, our empirical tests also point to a dichotomy between positive and negative beta firms, consistent with the mechanism we presented.

4.4 Additional evidence: Major events and public rating

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 global and local downturns. In our model, firms that take on more FX risk through a higher share

[36]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, the covariance between cash flow and exchange rate makes no qualitative difference.

of foreign currency debt can weather these episodes better compared to firms with lower foreign currency debt: they generate both higher earnings.

In this section, we repeat the same prediction exercise, but focusing on country-specific episodes of large currency depreciation, as well as global and EM-wide crisis events, including the Great Financial Crisis, the COVID-19 crisis, and the 2015 emerging market currency depreciation.[37] We follow the same predictive regression 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$_{f,t-1,t}$.

The results are again in line with our predictions, reported in Appendix D, Table C4. Firms in the non-tradable sector with higher foreign currency or hard currency share perform better in terms of higher earnings during large local currency depreciation episodes. This remains the case when we restrict the sample further to 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.

We use our empirical framework to provide one more piece of evidence in support of the signaling channel and report the results in Table C5 in Appendix D. We follow Sufi (2007) and Hale and Santos (2009) to measure information asymmetry faced by each firm using credit rating history. At each year t, firms are split into those that have received a public credit rating and those that have not yet been rated.[38] We run the predictive regressions separately on each sample. We find that the positive predictive relationship between FC shares and future earnings is driven by firms

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

[38]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".

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.

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:

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* $(\beta, \mu, \varepsilon)$*, 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, proved in Appendix C, 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 4, 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 US dollar-denominated borrowing and local currency, weighted by the size of each issuance. Similar to our treatment of firm-level outcomes and controls, both variables are winsorized at 2.5% and 97.5% tails.[39]

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)) does not affect the validity of our finding.

[39] Appendix D.1 offers more detail on how we extract pricing information from the raw Capital IQ debt structure module.

Table 4: Costly signaling: Testing model predictions on prices

VARIABLES	(1) FC-LC spread$_t$ (%)	(2) FC-LC spread$_t$ (%)	(3) FC-LC spread$_t$ (%)	(4) FC-LC spread$_t$ (%)
rolling $\beta_{f,t}$	-0.2447***	-0.6227***	-0.2834***	-0.5640***
	(0.0849)	(0.1632)	(0.0995)	(0.1942)
FC-LC residual maturity difference$_t$ (years)	0.0482**	0.0056	0.0349	-0.0366*
	(0.0223)	(0.0212)	(0.0265)	(0.0176)
FC share$_t$ (%)			0.0011	0.0059
			(0.0048)	(0.0097)
Observations	1,195	754	1,077	675
R-squared	0.5568	0.7770	0.5663	0.7888
Country*Industry*Year FE	✓	✓	✓	✓
Firm FE	-	✓	-	✓
Firm-level controls	-	-	✓	✓
No. clusters	34	23	32	20
No. FEs	437	493	403	445

Note: Table 4 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 new issuance. 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) and (3) report panel regression results with country-industry-year fixed effect to account for, among other things, expected local currency depreciation. Columns (2) and (4) add 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.

4.6 Alternative explanations and robustness checks

We discuss alternative explanations to our empirical results and provide additional robustness checks in this section.

Alternative explanations Our model and empirical tests focus on establishing a direct linkage between future firm performance and current foreign currency leverage, and we interpret the predictive relationship as supporting the signaling channel of debt currency choice. We explore a number of other factors that may also affect currency choice through various channels but do not mute the signaling channel.

Productive firms exploiting borrowing cost differential. Salomao and Varela (2022) propose a theory in which firms with high marginal product of capital (MPK) achieve an optimal scale faster when borrowing in foreign currency debt due to the cost advantage of foreign currency debt in the face of deviations from interest rate parity.

While our model predictions do not depend on the existence of exogenous UIP deviations, we nevertheless conduct two more empirical exercises to highlight the distinction of our theory. First, while our baseline specification already accounts for macro-level foreign currency cost advantages through Country×Industry×Year fixed effect, in Table C6, we show that there is, in general, no significant evidence that a larger cost differential in favor of foreign currency (USD) borrowing predicts higher earnings going forward for a given level of foreign currency debt share. While Column (5) of Panel (a) suggests that higher hard currency debt share predicts higher earnings when UIP deviations are high, the base level coefficient on hard currency debt share is still positive and significant. Taken together, these results are consistent with the finding of Gutierrez et al. (2023) using Peruvian data, that macro-level UIP deviations are unlikely to act as an important driver of cross-sectional differences in foreign currency leverage on their own.

Second, in Panel (a) of Table C7, we show that adding firms' marginal product of capital as an additional control in our predictive regression does not affect our conclusion.[40] Additionally, Column (2) of Panel (b), Table C7 shows that there is no evidence that high MPK interacted with high foreign currency debt share predict even higher earnings going forward beyond what foreign currency debt share does on its own.

Leverage as a signaling device. Hennessy et al. (2010) develop a dynamic model of repeated signaling in which firms with positive private information leverage up and underinvest. We show that adding leverage as a control in our predictive regressions does not affect our estimates (Panel (a), Table C7). Rather, leverage reinforces the foreign currency debt signaling channel, as indicated by the positive and significant interaction coefficient between foreign currency debt share and future earnings, as

[40]We measure a firm's MPK as log revenues minus log capital, following David et al. (2022) and Kilic and Tuzel (2024).

shown in Column (1) of Panel (b), Table C7.[41]

Debt specialization and currency choice. Colla et al. (2013) use public U.S. firm sample to show that most firms borrow in one type of debt. A diverse currency choice of debt reflects deviations from debt specialization, whose drivers include but are not limited to information asymmetry. We show in Panel (a) of Table C7 that another factor identified by Colla et al. (2013), the expected bankruptcy cost proxied by (the inverse of) firms' tangibility, does not affect the linkage between foreign currency debt share and future earnings, nor do we find evidence indicating that firms with lower bankruptcy cost and higher foreign currency share generate more earnings going forward (Column (3) of Panel (b), Table C7).[42]

Placebo tests In Table C8, we conduct two placebo tests to further support our findings. In Panel (a), we report the results from running the same predictive regressions (8) on firms listed domestically in Australia. Australian firms face similar dollar funding environment as the high-interest-rate Australia dollar is a popular vehicle for carry trade. These firms, however, arguably suffer less from asymmetric information compared to their emerging market counterparts. Panel (a) shows that there is little evidence that foreign currency share of Australian firms predict earnings going forward. In fact, the coefficient on hard currency, through which Australian firms could get cheaper funding, is negative. This further establishes the distinct role of information asymmetry in driving foreign currency borrowing of EM firms. In Panel (b), we replace future earnings to lagged earnings, to show that the lead-lag relationship in the data between past earnings and future foreign currency borrowing is only strong when we use foreign currency share to predict future earnings.

Robustness 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.

[41] We define leverage as long-term debt plus current liabilities, normalized by total assets and winsorize the measure following Giroud and Mueller (2021).

[42] Tangibility is measured using a firm's net property, plant and equipment.

Our baseline predictive regression specification (8) includes firm fixed effect and current level of earnings. While our primary focus is not the autoregressive coefficient on current earnings, and the correlation between foreign-currency share and current earnings is small, we nevertheless implement bias correction on Table 3 following the split-panel jackknife procedure introduced by Dhaene and Jochmans (2015). Figure C3 shows that the induced Nickell bias is small and, in most cases, leads to an *underestimate* of the linkage between foreign currency debt share and future earnings.

In Table C9, we provide additional robustness checks where we perform our predictive regression exercise on various subsamples of firms in our data. Panel (a) restricts attention to firms with a negative stock return-exchange rate beta based only on the level of the estimates. In Panel (b), we remove companies that are subsidiaries of some ultimate parent firms. We improve on the original Capital IQ data, sourcing ownership, and merger & acquisition information to dynamically identify subsidiaries.[43] Panel (c) and (d) show that our results are not driven by a small number of countries in our sample. We drop South Korea and India based on Figure C2(b), in which we see a large presence of firms from these two countries. We drop Colombia and Indonesia based on Table C1, where we see these two countries display a large discrepancy between the local currency debt share aggregated from our microdata and alternative data sources. The absence of these countries does not materially impact the results. Panel (e) explores alternative clustering in calculating the standard errors. Panel (f) shows that the predictive relationship remains robust if we focus on the share of foreign currency bank loans among all loans or remove firm-year observations with no borrowing in foreign currency bonds and notes. Finally, Panel (g) demonstrates the robustness of our results when we remove firm fixed effect from the estimation.

5 Conclusion

This paper is motivated by the observation that corporates in emerging market economies, for which borrowing in local currency would provide greater hedging benefits, actually borrow more in foreign

[43]Capital IQ assigns static status indicator to firms based on the year of the data vintage. Firms identified as operating subsidiaries appearing in our baseline sample are typically acquired by other firms in the middle of our sample period. As these firms are delisted following the acquisition, they drop out of our baseline regression sample after the acquisition and thus avoid being double-counted.

currency. 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. Our model also provides a rationale for why emerging market firms forgo hedging their currency exposures as a growing literature documents.

We present empirical evidence to provide support for the signaling channel in our model. We test the predictions of our model also comparing it to those of other alternative mechanisms. In addition, we also restrict our attention to cases for which we expect information asymmetries to matter more, such as the case of unrated firms. We also provide a number of robustness checks. 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. Nevertheless, large shocks could 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.

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Internet Appendix

A Theory Appendix

A.1 Equilibrium definition and intermediate lemmas

In this section. We formally define the equilibrium and introduce some intermediate results helpful for proving the propositions in Section 3.

Definition A.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* $\mu = \mu_*$*.*[44]
- *debt pricing functions are rational and satisfy*

$$P(\alpha) = E[(1 - \Phi(Z(\alpha, \varepsilon), \mu(\alpha), \varepsilon))], \ P_{\$}(\alpha) = E[\varepsilon(1 - \Phi(Z(\alpha, \varepsilon), \mu(\alpha), \varepsilon))], \tag{9}$$

where $\mu(\alpha) = A^{-1}(\alpha)$ *if the inverse of* $A(\mu)$*;*

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

- *the fraction $A(\mu)$ is optimal for the firm given the debt pricing functions (9):*

$$A(\mu) \;=\; \arg\max_{\alpha>0} E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu,\varepsilon)]\,. \tag{10}$$

and

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

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

Lemma A.2 provides a method to construct the equilibrium we characterized. We follow this lemma to compute numerically the equilibrium foreign currency debt share plotted in Figure 2.

Lemma A.2 *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 (15). And then, α^* is defined as the unique solution to

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

where $E(\mu)$ is defined in (7). In the monotone increasing equilibrium, we first do the transformation to $\tilde{\alpha}=1/\alpha$ and then proceed as above.

A.2 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

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

whereas

$$\begin{aligned} 0 \;\le\; (\log\tilde{\eta})_{x\varepsilon} \;&=\; (\log(\eta(\tilde{x}/\tilde{\varepsilon},\mu,1/\tilde{\varepsilon}) - 3\log\tilde{\varepsilon}))_{x\varepsilon} \\ &=\; -\tilde{\varepsilon}^{-2}(\log\eta)_{x\varepsilon} \;-\; \tilde{x}\tilde{\varepsilon}^{-2}(\log\eta)_{\mu x} - \tilde{x}/\tilde{\varepsilon}^{2}(\log\eta)_{xx} \;-\; \tilde{\varepsilon}^{-3}(\log\eta)_{x\varepsilon}\,. \end{aligned} \tag{11}$$

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 Introducing UIP deviations

We assume that all market participants are risk-neutral, fully rational and discount the future at zero rate. Under this assumption, the bond price schedules are given by

$$P(\alpha) \;=\; \xi E[(1-\Phi(Z(\alpha,\varepsilon),\mu,\varepsilon))|\alpha],\;\; P_{\$}(\alpha) \;=\; E[\varepsilon(1-\Phi(Z(\alpha,\varepsilon),\mu,\varepsilon))|\alpha] \tag{12}$$

where ξ is a wedge reflecting UIP deviations. The firm defaults if and only if cash flows X are below the total debt face value given by

$$Z(\alpha,\varepsilon) \;\equiv\; B(\alpha) + \varepsilon B_{\$}(\alpha) \;=\; (1+\alpha\varepsilon)B(\alpha) \;=\; (1+\alpha\varepsilon)I/\bar{P}(\alpha)\,, \tag{13}$$

with $\bar{P}(\alpha) = P(\alpha) + \alpha P_{\$}(\alpha)$. Conditional on α, shareholders' equity value is given by $E[\Psi(Z(\alpha, \varepsilon), \mu, \varepsilon)]$. First, the aggregate debt pricing function satisfies

$$\bar{P}(\alpha) \;=\; E[(\xi + \varepsilon\alpha)(1 - \Phi((1 + \alpha\varepsilon)I/\bar{P}(\alpha), \mu(\alpha), \varepsilon)) \,. \tag{14}$$

Define $F(x, y)$ implicitly to be the unique[45] solution to

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

Then, (5) implies that in a separating equilibrium, the mapping between the foreign currency debt ratio and the hidden type of firms $\mu(\alpha)$ satisfies $\mu(\alpha) \;=\; F(\bar{P}(\alpha),\, \alpha)\,.$

To find the equilibrium debt price, we use the first order conditions for the firm in (10): 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 (14), Proposition B.1 characterizes the equilibrium price of debt.

Proposition B.1 (Equilibrium debt pricing with UIP deviations) *In any candidate equilibrium, the price $\bar{P}(\alpha)$ satisfies the ordinary differential equation*

$$\bar{P}'(\alpha) \;=\; E[\varepsilon(1 - \Phi((I/\bar{P}(\alpha))(1 + \varepsilon\alpha), F(\bar{P}(\alpha),\, \alpha), \varepsilon))]\,, \tag{15}$$

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

C Proofs

We will be extensively using the following technical lemma.

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

Lemma C.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 C.1.

Lemma C.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 3.1. 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

$$\begin{aligned}
0 \;&=\; -E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))(-I\bar{P}'(\alpha)\bar{P}(\alpha)^{-2}(1+\varepsilon\alpha)+I\bar{P}(\alpha)^{-1}\varepsilon)] \\
&=\; -I\bar{P}'(\alpha)\bar{P}(\alpha)^{-2}\underbrace{E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))(1+\varepsilon\alpha)]}_{=\bar{P}(\alpha)} \\
&+\; I\bar{P}(\alpha)^{-1}E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))\varepsilon] \\
&=\; I\bar{P}(\alpha)^{-1}(-\bar{P}'(\alpha)+E[(1-\Phi(I\bar{P}(\alpha)^{-1}(1+\varepsilon\alpha),\mu,\varepsilon))\varepsilon])\,,
\end{aligned} \tag{16}$$

and the claim follows. Q.E.D.

Proof of Proposition 3.2. We have

$$\mu'(\alpha) \ = \ \frac{d}{d\alpha}F = \ F_x \bar{P}'(\alpha) \ + \ F_y\,. \tag{17}$$

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 3.1, 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

$$\begin{aligned} \mu'(\alpha) \ &= \ \frac{E[(1-I^{-1}z^2\eta(z))]}{-E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x, \ F, \ \varepsilon)]}E[\varepsilon(1-\Phi(z))] \\ &+ \ \frac{E[\varepsilon((1-\Phi(z) - z\eta(z))]}{E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x, \ F, \ \varepsilon)]} \\ &= \ \frac{-I^{-1}E[z^2\eta(z)]\,E[\varepsilon(1-\Phi(z))] \ + \ E[\varepsilon z\eta(z)]}{-E[(1+\varepsilon y)\Phi_\mu((1+\varepsilon y)I/x, \ F, \ \varepsilon)]}\,. \end{aligned} \tag{18}$$

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

$$\begin{aligned}
\psi(\alpha) \;&\equiv\; -I^{-1}E[(I/\bar{P})^2(1+\varepsilon\alpha)^2\eta((I/\bar{P})(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi((I/\bar{P})(1+\varepsilon\alpha)))]\\
&+\; E[\varepsilon(I/\bar{P})(1+\varepsilon\alpha)\eta((I/\bar{P})(1+\varepsilon\alpha))]\\
&=\; I/(\bar{P})^2\Big(-E[(1+\varepsilon\alpha)^2\eta((I/\bar{P})(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi((I/\bar{P})(1+\varepsilon\alpha)))]\\
&+\; E[\varepsilon(1+\varepsilon\alpha)\eta((I/\bar{P})(1+\varepsilon\alpha))]\bar{P}\;\Big)\\
&=\; I/(\bar{P})^2\Big(-E[(1+\varepsilon\alpha)^2\eta(\kappa(1+\varepsilon\alpha))]\,E[\varepsilon(1-\Phi(\kappa(1+\varepsilon\alpha)))]\\
&+\; E[\varepsilon(1+\varepsilon\alpha)\eta(\kappa(1+\varepsilon\alpha))]E[(1+\varepsilon\alpha)(1-\Phi(\kappa(1+\varepsilon\alpha)))]\Big)
\end{aligned} \tag{19}$$

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 (19) 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 C.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,

$$\frac{d}{d\varepsilon}((1+\varepsilon\alpha)h(\kappa(1+\varepsilon\alpha))) \;=\; \alpha h \;+\; \kappa\alpha(1+\varepsilon\alpha)h_x \;+\; (1+\varepsilon\alpha)h_\varepsilon\,, \tag{20}$$

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 (20) are positive, and therefore (20) is positive.

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

$$\frac{d}{d\alpha}E[\Psi((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon)] \;=\; \mu'(\alpha)\,E[\Psi_\mu((1+\alpha\varepsilon)I/\bar{P}(\alpha),\mu(\alpha),\varepsilon)]\,. \tag{21}$$

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 C.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 C.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 C.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

$$E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))(B'(\alpha)(1+\varepsilon\alpha)+B(\alpha)\varepsilon)] \ < \ 0 \tag{22}$$

for $\alpha < A(\mu)$ and that the sign flips for $\alpha > A(\mu)$. Equivalently, we can rewrite the optimality condition (22) for $\alpha < A(\mu)$ as

$$\frac{B'(\alpha)}{B(\alpha)} \ < \ -\frac{E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]}{E[(1+\varepsilon\alpha)\,(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]},\ \alpha < A(\mu). \tag{23}$$

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 (23) for $\mu > \mu(\alpha)$. Since (23) 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

$$\begin{aligned} &-E[\varepsilon\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]E[(1+\varepsilon\alpha)(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))] \\ &+E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]E[(1+\varepsilon\alpha)\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)] \ \le \ 0\,, \end{aligned} \tag{24}$$

which is equivalent to

$$\begin{aligned} &-E[\varepsilon\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)]E[(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))] \\ &+E[\varepsilon(1-\Phi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon))]E[\Phi_\mu(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon)] \ \le \ 0\,, \end{aligned} \tag{25}$$

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 C.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 C.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 C.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 C.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

$$\frac{\Phi_\mu(x, \mu, \varepsilon)}{1-\Phi(x, \mu, \varepsilon)} \ = \ \frac{-\int_x^\infty \eta_\mu(y|\mu,\varepsilon)dy}{\int_x^\infty \eta(y|\mu,\varepsilon)dy} \tag{26}$$

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 C.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 3.3. 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 3.2, 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 C.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 C.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 3.4. We have

$$\begin{aligned}\frac{\partial}{\partial\varepsilon}\Psi(B(\alpha)(1+\varepsilon\alpha),\mu,\varepsilon) &= \frac{\partial}{\partial\varepsilon}\int_{B(\alpha)(1+\varepsilon\alpha)}^{\infty}(y-x)\eta(y|\mu,\varepsilon)dy \\ &= \int_{B(\alpha)(1+\varepsilon\alpha)}^{\infty}(y-x)\frac{\partial}{\partial\varepsilon}\eta(y|\mu,\varepsilon)dy\end{aligned} \tag{27}$$

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

$$\begin{aligned}P_{\$}(\alpha) &= E[\varepsilon E[\mathbf{1}_{(1+\alpha\varepsilon)I/\bar{P}(\alpha)<x}|\varepsilon]] \\ &\leq E[\varepsilon]E[\mathbf{1}_{(1+\alpha\varepsilon)I/\bar{P}(\alpha)<x}] = E[\varepsilon]P(\alpha)\end{aligned} \tag{28}$$

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.

D Data appendix, additional tables from empirical analysis

D.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 public sector (two-digit SIC code bigger than 90) and in the financial sector (two-digit SIC code from 60 to 69), but preserve real estate firms (SIC code 65). 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). The raw data contains duplicates due to fiscal year/quarter inconsistencies. We develop an algorithm to restore uniqueness.

Debt structure data and debt pricing We take the following steps to clean up the Capital IQ debt structure module. Our procedure is consistent with recent efforts to construct time-consistent international credit microdata, as in Boyarchenko and Elias (2023). We drop duplicates using the same algorithm we applied to the financial data. We also pay attention to additional duplicates in the debt structure module: For credit lines, Capital IQ reports both the maximum amount to be drawn and the outstanding balance. Simply aggregating the observations to the firm level introduces double counting. Accordingly, we only retain information on the amount outstanding prior to calculating foreign currency debt share.

To generate Table 4, we restrict attention to initial issuance. Following Boyarchenko and Elias (2023), we identify initial issuance as the first time a loan/bond (marked by `componentid` in the data) appears in our full dataset (our sample is a subset of the full data). Boyarchenko and Elias (2023) conduct cross-check to show that this procedure yields reliable identification of initial issuance.

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).[46] 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 for the countries in our sample 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

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

the stock price recorded at the end of the companies' year-end when computing market caps and merging with Capital IQ financial data.

D.2 Additional tables and figures

Figure C4 reports 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: Capital IQ coverage: Benchmarking with aggregate estimates

Country	Local currency share (%, GDM)	Local currency share (%, Capital IQ)	Aggregate debt in Capital IQ (% of GDM)
AR	62.1	46.3	35.6
BR	71.5	72.5	71.4
CL	69.1	45.8	70.6
CO	76.2	52.2	45.4
CZ	68.0	49.4	13.2
HU	46.9	35.9	6.3
ID	63.1	37.5	89.5
IL	67.7	56.6	49.0
IN	86.6	84.8	41.5
KR	78.5	83.5	59.2
MX	39.3	36.7	117.1
MY	81.8	67.7	74.7
PE	35.3	34.5	73.4
PL	69.5	68.9	16.3
RU	62.3	48.7	34.8
TH	85.0	77.6	43.0
TR	51.7	36.5	18.8
ZA	65.6	63.2	83.2

Note: Table C1 compares the size and currency composition of country-level corporate debt computed from Capital IQ to the data from the Institute of International Finance's Global Debt Monitor (GDM).

Table C2: Signaling channel of foreign-currency debt: Baseline predictive regressions (full table)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			positive FC	domestic			add positive β
	all sectors	nontradable	nontradable	nontradable	nontradable	nontradable	all sectors
VARIABLES	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.009**	0.009**	0.009***			0.005**
	(0.002)	(0.003)	(0.004)	(0.003)			(0.002)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.003)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.006*	
						(0.003)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.016**
							(0.007)
$\beta_{f,t} > 0$, significant							0.724
							(0.581)
EBIT$_{f,t}$ / Asset$_{f,t}$ (%)	0.389***	0.358***	0.321***	0.369***	0.358***	0.360***	0.390***
	(0.014)	(0.022)	(0.027)	(0.020)	(0.022)	(0.022)	(0.015)
yoy stock return$_{f,t}$	0.006***	0.008***	0.011***	0.008***	0.008***	0.008***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
current ratio$_{f,t}$	-0.353***	-0.269***	-0.095**	-0.274***	-0.269***	-0.286***	-0.348***
	(0.043)	(0.051)	(0.045)	(0.052)	(0.050)	(0.056)	(0.045)
z-score$_{f,t}$	0.047	0.096	0.155**	0.082	0.097	0.112	0.051
	(0.045)	(0.063)	(0.068)	(0.065)	(0.063)	(0.070)	(0.045)
log capex$_{f,t}$	-0.036	-0.052	-0.009	-0.054	-0.052	-0.059	-0.033
	(0.039)	(0.050)	(0.083)	(0.053)	(0.051)	(0.054)	(0.039)
log total liabilities$_{f,t}$	-0.792***	-0.322	-0.200	-0.362*	-0.316	-0.323	-0.769***
	(0.133)	(0.196)	(0.320)	(0.195)	(0.195)	(0.215)	(0.134)
log market cap$_{f,t}$	0.345***	0.244	-0.252	0.275*	0.244	0.265	0.329***
	(0.074)	(0.153)	(0.253)	(0.150)	(0.151)	(0.163)	(0.077)
rolling $\beta_{f,t}$	0.001	0.067	-0.007	0.069	0.066	0.056	-0.001
	(0.022)	(0.048)	(0.089)	(0.047)	(0.048)	(0.046)	(0.020)
Observations	50,224	17,502	9,007	17,254	17,502	17,140	50,821
R-squared	0.709	0.731	0.768	0.730	0.732	0.733	0.709
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
No. clusters	57	37	33	37	37	37	57
No. FEs	10670	4810	3350	4744	4810	4771	10801

Note: Table C2 reports panel regressions relating foreign currency share of outstanding debt to future earnings. Compared to Table 3, this table also reports the coefficients associated with the control variables. 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) includes firms in both tradable and nontradable sectors defined by Aguiar and Gopinath (2005). Column (2) focuses on nontradable sectors. Column (3) restricts the sample to firm-year observations with non-zero foreign currency borrowing. Column (4) excludes firms listed overseas. In columns (5) and (6), the variable of interest is the share of hard currency debt and yearly changes in foreign currency debt share. In column (7), we introduce firm-year observations with a statistically significantly positive β and interact with a dummy indicating this positive β with foreign currency debt share. Standard errors are clustered at the industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C3: Consistency check: Predictive regressions removing observations with debt structure inconsistent with aggregate debt

	(1)	(2)	(3)
	nontradable	nontradable	nontradable
	25%	10%	5%
VARIABLES	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.008**	0.007*	0.007*
	(0.004)	(0.004)	(0.004)
Observations	16,831	16,033	15,255
R-squared	0.732	0.734	0.738
Country*Industry*Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Firm controls	✓	✓	✓
No. clusters	37	37	37
No. FEs	4724	4618	4518

Note: Table C3 repeats the exercise of Table 3, column (2), 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 (3) in each panel, we progressively drop observations whose deviations (absolute values normalized by the bottom-up aggregates) are larger than 25%, 10%, and 5%. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Testing the Signaling channel: Major events

VARIABLES	(1) nontradable depreciation episodes $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable and domestic depreciation episodes $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) nontradable 2007/2014/2019 $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) nontradable and domestic 2007/2014/2019 $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.008	0.009*	0.015*	0.015*
	(0.005)	(0.005)	(0.008)	(0.008)
Observations	3,466	3,430	2,880	2,853
R-squared	0.702	0.703	0.832	0.832
Country*Industry FE	✓	✓	-	-
Country*Industry*Year FE	-	-	✓	✓
Firm FE	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓
No. clusters	40	40	126	126
No. FEs	1190	1175	1702	1688

Note: Table C4 report predictive regression results focusing our sample on important emerging market currency volatility events. In columns (1) and (2), "depreciation episodes" refer to years for which the firms' local currency depreciates by more than 10% year over year. Columns (3) to (4) focus on predicting earnings in the years 2008, 2015, and 2020 (Great Financial Crisis, EM currency crises, and COVID-19) based on the previous years' foreign currency debt share. 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. Standard errors clustered at the industry level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C5: Testing the signaling channel: Public rating

	(1)	(2)	(3)	(4)
			nontradable	nontradable
	unrated	rated	unrated	rated
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$_{f,t}$ (%)	0.005**	0.002	0.008**	0.006
	(0.002)	(0.006)	(0.003)	(0.006)
Observations	46,509	2,475	15,499	1,296
R-squared	0.705	0.856	0.728	0.870
Country*Industry*Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
No. clusters	57	27	37	15
No. FEs	10200	1096	4521	573

Note: Table C5 report the results from predictive regressions on negative-β firms that have or have not received a public credit rating as of each year in our sample period to test the potential role of asymmetric information in driving currency choices, following Sufi (2007). Columns (1) and (3) report results for the unrated firms. Columns (2) and (4) report results for the rated firms. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Borrowing cost advantages and the signaling channel

VARIABLES	(1) all sectors $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) positive FC nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) domestic nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.007*	0.005	0.008*		
	(0.002)	(0.004)	(0.005)	(0.004)		
fc share × 1y UIP deviations (%)	0.000	0.000	0.001	0.001		
	(0.000)	(0.000)	(0.001)	(0.000)		
hard currency share$_{f,t}$ (%)					0.009**	
					(0.004)	
hc share × 1y UIP deviations (%)					0.001**	
					(0.000)	
Δ foreign currency share$_{f,t-1,t}$ (%)						0.006
						(0.004)
Δ fc share × 1y UIP deviations (%)						0.000
						(0.001)
Observations	50,224	17,502	9,007	17,254	17,502	17,140
R-squared	0.709	0.732	0.768	0.730	0.732	0.733
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓
No. clusters	57	37	33	37	37	37
No. FEs	10670	4810	3350	4744	4810	4771

Note: Table C6 augments the baseline predictive regression (8) by interacting foreign (hard) currency share with 1-year deviations from uncovered interest parity for the home currency of each firm. The UIP deviations are calculated using the exchange rate forecast provided by FX4Cast. 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. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table C7: Additional exploration: MPK, leverage and tangibility

(a) Without interacting with foreign currency share

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) positive FC nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.008**	0.009**	0.008***			0.005**
	(0.002)	(0.003)	(0.004)	(0.003)			(0.002)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.003)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.006*	
						(0.003)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.016**
							(0.008)
$\beta_{f,t} > 0$, significant							0.649
							(0.593)
MPK$_{f,t}$	1.324***	0.932***	0.867**	0.902***	0.937***	0.913***	1.327***
	(0.203)	(0.285)	(0.414)	(0.287)	(0.284)	(0.287)	(0.203)
leverage$_{f,t}$	3.316***	4.814***	5.444***	4.915***	4.796***	4.909***	3.285***
	(0.549)	(0.761)	(1.447)	(0.802)	(0.752)	(0.732)	(0.554)
tangibility$_{f,t}$	0.008*	0.008	0.009	0.011*	0.009	0.007	0.008*
	(0.004)	(0.006)	(0.010)	(0.006)	(0.006)	(0.006)	(0.004)
Observations	49,943	17,394	8,956	17,168	17,394	17,037	50,540
R-squared	0.711	0.736	0.772	0.734	0.736	0.738	0.711
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	57	37	33	37	37	37	57
No. FEs	10625	4793	3337	4734	4793	4754	10756

Note: See table note after the panel (b) for a detailed description.

Table C7: Additional exploration: MPK, leverage and tangibility (continued)

(b) Interacting with foreign currency share

VARIABLES	(1) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	-0.004	0.009**	0.011**
	(0.006)	(0.004)	(0.004)
fc share$_{f,t}\times$ leverage$_{f,t}$	0.028*		
	(0.014)		
fc share$_{f,t}\times$ mpk$_{f,t}$		0.003	
		(0.003)	
fc share$_{f,t}\times$ tangibility$_{f,t}$			-0.000
			(0.000)
Observations	17,394	17,394	17,394
R-squared	0.737	0.736	0.736
Country*Industry*Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Firm controls	✓	✓	✓
No. clusters	37	37	37
No. FEs	4793	4793	4793

Note: Table C7 augments the baseline predictive regression (8) with additional firm-level regressors that may explain foreign currency choice (marginal product of capital, see Salomao and Varela (2022)), debt as a signaling device (leverage, see Hennessy et al. (2010)), and debt specialization (tangibility of firms, see Colla et al. (2013)). Panel (a) reports results by adding these metrics as controls, and Panel (b) interacts with these metrics with foreign-currency debt share. The marginal product of capital (MPK) is defined as log sales over capital (David et al., 2022; Kilic and Tuzel, 2024). Leverage is the sum of long-term debt and current liabilities divided by total assets. Following Giroud and Mueller (2021), we replace leverage above 100% to 100%. Tangibility is defined as net property, plant, and equipment normalized by total assets.

Table C8: Placebo tests

(a) Australian firms

VARIABLES	(1) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(3) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	(4) nontradable $\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.003			0.008
	(0.019)			(0.016)
hard currency share$_{f,t}$ (%)		-0.003		
		(0.029)		
USD share$_{f,t}$ (%)			0.001	
			(0.038)	
$\beta_{f,t} > 0$, significant				1.572
				(3.606)
FC share × ($\beta_{f,t} > 0$, significant)				-0.015
				(0.037)
Observations	1,963	1,963	1,963	2,800
R-squared	0.561	0.561	0.561	0.593
Industry*Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
No. clusters	21	21	21	36
No. FEs	538	538	538	818

(b) Lagged earnings and foreign currency share

VARIABLES	(1) EBIT to asset nontradable t-1	(2) EBIT to asset nontradable t-1	(3) EBIT to asset nontradable t-2	(4) EBIT to asset nontradable t-2
foreign currency share$_{f,t}$ (%)	0.001	0.001	-0.004	-0.004
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	20,936	20,936	19,651	19,651
R-squared	0.671	0.671	0.676	0.676
Country*Industry*Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firm controls	-	✓	-	✓
No. clusters	37	37	37	37
No. FEs	5315	5315	5088	5088

Note: Table C8 reports the results from a set of placebo tests. In Panel (a), we replicate our baseline predictive regressions on Australian firms listed domestically. These firms face similar dollar funding condition as the emerging market firms do, but may suffer less from information asymmetry. In Panel (b), we show that there is no systematic relationship between past earnings and current foreign-currency debt share. In columns (2) and (4), we control for current realizations of the control variables used in the baseline regression (8).

Table C9: Miscellaneous robustness checks

(a) Alternative definition of stock return-depreciation β

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) positive FC nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.006***	0.008**	0.008*	0.008**			0.005**
	(0.002)	(0.004)	(0.004)	(0.004)			(0.002)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.003)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.007**	
						(0.003)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.002
							(0.004)
$\beta_{f,t} > 0$, significant							0.033
							(0.282)
Observations	46,415	16,116	8,347	15,909	16,116	15,798	50,821
R-squared	0.713	0.738	0.777	0.736	0.738	0.739	0.709
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	55	35	32	35	35	35	57
No. FEs	10134	4517	3137	4464	4517	4484	10801

(b) Remove operating subsidiaries

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) positive FC nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005*	0.009*	0.014**	0.008*			0.005*
	(0.003)	(0.004)	(0.006)	(0.004)			(0.003)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.004)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.009**	
						(0.004)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.030***
							(0.008)
$\beta_{f,t} > 0$, significant							1.034
							(1.009)
Observations	32,777	11,102	5,287	10,914	11,102	10,838	33,116
R-squared	0.720	0.742	0.796	0.744	0.742	0.746	0.720
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	53	33	30	33	33	33	53
No. FEs	8210	3620	2337	3563	3620	3587	8297

Note: Table C9 reports the results of our robustness checks. Panel (a) repeats the baseline regression (8) on firms with a negative estimated stock return-depreciation β, i.e. we exclude those firms with an insignificantly positive β. Panel (b) removes firms that we identify as subsidiaries of some parent firms. In all panels, standard errors clustered on the industry are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C9: Miscellaneous robustness checks (continued)

(c) Drop Indian and South Korean firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			positive FC	domestic			add positive β
	all sectors	nontradable	nontradable	nontradable	nontradable	nontradable	all sectors
VARIABLES	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.004*	0.008**	0.009*	0.009**			0.004*
	(0.002)	(0.004)	(0.004)	(0.004)			(0.002)
hard currency share$_{f,t}$ (%)					0.011***		
					(0.004)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.007	
						(0.004)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.023***
							(0.009)
$\beta_{f,t} > 0$, significant							1.244
							(0.824)
Observations	25,972	12,422	6,817	12,231	12,422	12,228	26,470
R-squared	0.742	0.747	0.781	0.746	0.747	0.747	0.740
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	57	37	32	37	37	37	57
No. FEs	7112	3684	2597	3626	3684	3654	7239

(d) Drop Colombian and Indonesian firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			positive FC	domestic			add positive β
	all sectors	nontradable	nontradable	nontradable	nontradable	nontradable	all sectors
VARIABLES	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	$\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.008**	0.009**	0.008**			0.005**
	(0.002)	(0.004)	(0.004)	(0.004)			(0.002)
hard currency share$_{f,t}$ (%)					0.010**		
					(0.004)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.007*	
						(0.003)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.019**
							(0.007)
$\beta_{f,t} > 0$, significant							0.775
							(0.615)
Observations	46,893	15,759	7,777	15,511	15,759	15,412	47,436
R-squared	0.705	0.727	0.764	0.725	0.727	0.729	0.704
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓
No. clusters	54	34	31	34	34	34	54
No. FEs	9780	4317	2952	4251	4317	4279	9904

Note: Table C9 reports the results of our robustness checks. Panels (c) and (d) drop countries that either comprise a large share of firms in the sample (India and South Korea) or with an aggregated corporate local currency debt share substantially (> 20%) different from IIF's Global Debt Monitor (Colombia and Indonesia, see Table C1). In all panels, standard errors clustered on the industry are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C9: Miscellaneous robustness checks (continued)

(e) Alternative clustered standard errors

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(7) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(8) add positive β all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.005**	0.009**	0.009**	0.005**	0.005***	0.009***	0.009***	0.005***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
FC share × ($\beta_{f,t} > 0$, significant)				-0.016*				-0.016
				(0.008)				(0.010)
Observations	50,224	17,502	17,254	50,821	50,224	17,502	17,254	50,821
R-squared	0.709	0.731	0.730	0.709	0.709	0.731	0.730	0.709
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Firm Year	Firm Year	Firm Year	Firm Year
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
No. clusters	16	16	16	16	16	16	16	16
No. FEs	10670	4810	4744	10801	10670	4810	4744	10801

(f) Foreign currency bank loan and bond

VARIABLES	(1) all sectors $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(2) nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(3) domestic nontradable $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(4) all sectors no fc bond $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(5) nontradable no fc bond $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)	(6) domestic nontradable no fc bond $\frac{EBIT_{f,t+1}}{Asset_{f,t+1}}$ (%)
foreign currency share$_{f,t}$ (%)				0.005**	0.008**	0.009**
				(0.002)	(0.004)	(0.004)
fc share$_{f,t}$ (bank loan, %)	0.003	0.007*	0.007**			
	(0.002)	(0.003)	(0.003)			
Observations	48,228	16,582	16,369	44,369	14,639	14,441
R-squared	0.704	0.727	0.724	0.710	0.737	0.735
Firm-level Controls	✓	✓	✓	✓	✓	✓
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
No. clusters	57	37	37	57	37	37
No. FEs	10423	4659	4604	9932	4386	4339

Note: Table C9 reports the results of our robustness checks. Panel (e) reports predictive regressions using alternative clustered standard errors. The first four columns report two-way clustered standard errors at the industry and year levels. The row "number of clusters" corresponds to the number of year clusters. The last four columns report two-way clustered standard errors at firm and year levels. Panel (f) investigates the predictive relationship between foreign-currency bank loans and future earnings. The first three columns use the share of foreign-currency bank loans (as % of all loans) as the main regressor. In the last three columns, foreign currency debt share is the main regressor, but the sample is restricted to those that do not have foreign currency bonds and notes outstanding in their borrowing. "Domestic nontradable" are firms in the nontradable sector that exclude those that are not listed overseas. *** p<0.01, ** p<0.05, * p<0.1.

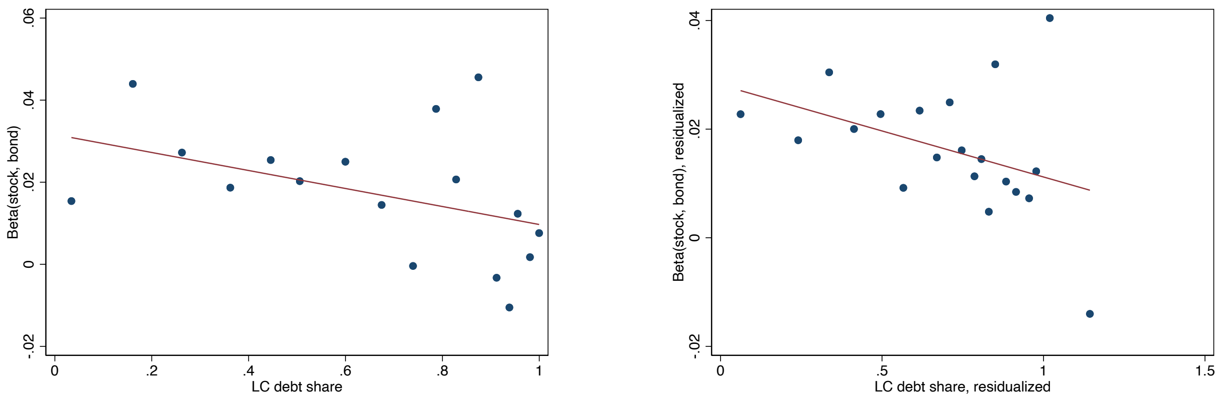
Table C9: Miscellaneous robustness checks (continued)

(g) Removing firm fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			positive FC	domestic			add positive β
	all sectors	nontradable	nontradable	nontradable	nontradable	nontradable	all sectors
VARIABLES	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)	$\frac{EBIT_{f.t+1}}{Asset_{f.t+1}}$ (%)
foreign currency share$_{f,t}$ (%)	0.002**	0.002	0.004*	0.003*			0.002**
	(0.001)	(0.002)	(0.002)	(0.002)			(0.001)
hard currency share$_{f,t}$ (%)					0.003		
					(0.002)		
Δ foreign currency share$_{f,t-1,t}$ (%)						0.007*	
						(0.004)	
FC share $\times$ ($\beta_{f,t} > 0$, significant)							-0.012*
							(0.007)
$\beta_{f,t} > 0$, significant							0.518**
							(0.240)
Observations	50,224	17,502	9,007	17,254	17,502	17,140	50,821
R-squared	0.626	0.647	0.673	0.647	0.647	0.649	0.626
Country*Industry*Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	-	-	-	-	-	-	-
No. clusters	57	37	33	37	37	37	57
No. FEs	5728	3005	2063	2980	3005	2977	5818

Note: Table C9 reports the results of our robustness checks. Panel (g) reports the results from removing firm fixed effect from the list of fixed effects included in the baseline predictive regression. Standard errors are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

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

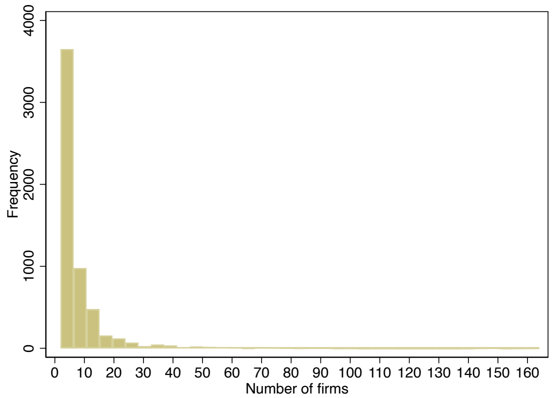


(a) Raw scatters

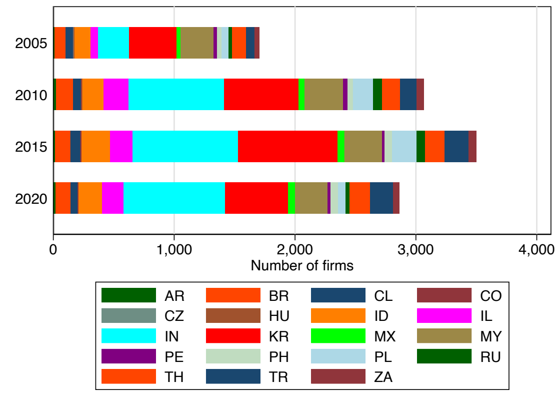
(b) Residualized by industry fixed effect

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 the 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 the average market capitalization of each firm.

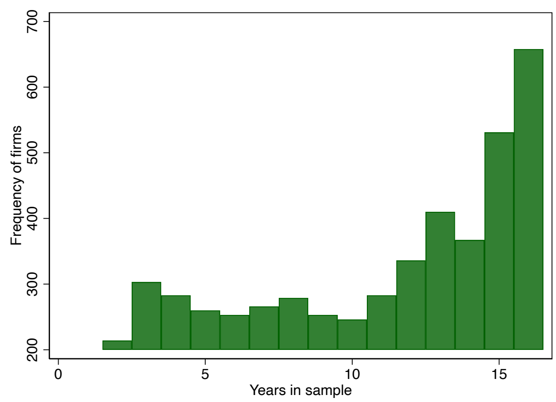
Figure C2: Regression sample: Additional summary statistics



(a) Number of firms within country-sector-year pairs

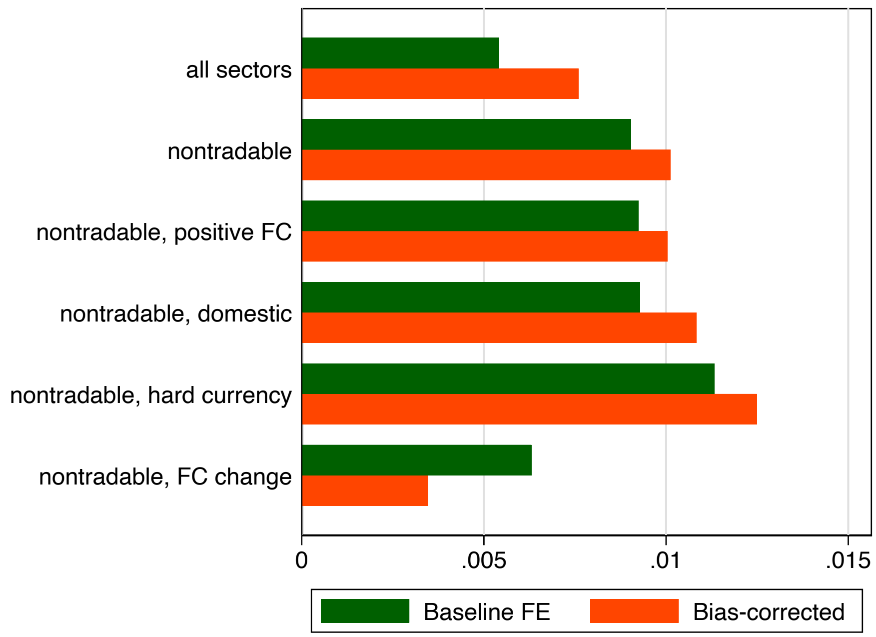


(b) Country distribution of firms in regression sample, selected years



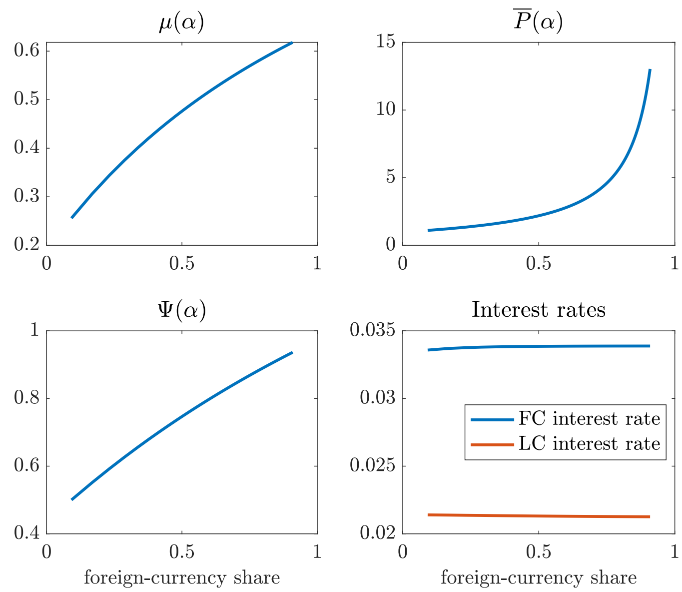
(c) Distribution of years in the sample for firms in regression sample

Figure C3: Baseline predictive regressions: Bias-corrected coefficients



Note: Figure C3 compares the point estimates from the baseline regressions (8) with a dynamic panel, firm fixed effect, and OLS (green bars) to those obtained using the Dhaene and Jochmans (2015) split-panel jackknife bias correction technique. The bias correction is achieved by separately estimating (8) via OLS with firm fixed effect for the first half of the panel and the second half of the panel and correcting the original estimate θ by the formula $2\theta - 0.5(\theta_1 + \theta_2)$, where θ_1 and θ_2 are the estimates from the first and second half of the panel. From the top to the bottom, the green bars correspond to columns (1) through (6) of Table 3.

Figure C4: 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 $\mathbb{E}[\varepsilon] \cdot P^{\$}(\alpha)^{-1} - 1$.