

COSTLY INFORMATION AND SOVEREIGN RISK ^{*}

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Grace Weishi Gu[†] and Zachary R. Stangebye[‡]

The consequences of costly information acquisition for sovereign risk are explored in a quantitative sovereign default model. We identify information costs empirically using Bloomberg news-heat data. The calibrated model microfounds heteroskedasticity in the country risk spread as measured by a novel metric we call the Crisis Volatility Ratio (CVR). Crises are endogenously more volatile because more information is acquired and priced. Re-calibrated extant models do not generate CVRs in the empirical range, but ours does. Because effective risk tolerance depends on the information set, the model also suggests that risk premia fall with information costs.

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[†]E-mail: grace.gu@ucsc.edu, Phone: (831) 459-4791, Address: 463 Engineering 2, 1156 High Street, Santa Cruz, CA 95064

[‡]E-mail: zstangeb@nd.edu, Phone: (574) 631-1054, Fax: (574) 631-1054, Address: 3015 Nanovic Hall, Notre Dame, IN 46556 (Corresponding Author)

1. Introduction

Yields in sovereign bond markets in emerging economies largely reflect the risk that a domestic borrower may default on foreign creditors since it does not in principle have any reason to care about the well-being of these creditors. But a sovereign borrower's lack of welfare concern for its foreign lenders is not the only relevant friction that arises from the international nature of these markets: Information frictions also play a large role in cross-border financial transactions: Foreign investors are likely to be less informed about payoff-relevant shocks in emerging/developing countries ([Hatchondo \[2004\]](#), [Van Nieuwerburgh and Veldkamp \[2009\]](#), or [Bacchetta and van Wincoop \[2010\]](#)). For instance, Bloomberg publication and readership data suggest that only 30.5% of articles published pertain to emerging and developing economies, despite the fact that 47 out of 61 countries in their dataset fall under this category.¹

This is true even for institutional investors, as few developing countries fully adopt International Public Sector Accounting Standards (IPSAS) or other international standards for government finance reporting. Further, their sovereign bonds are usually traded over-the-counter with limited information and thin trading volumes relative to assets traded in exchanges, such as stocks. Nevertheless, payoff-relevant information can often be acquired at a cost. For instance, institutions can spend resources to harmonize data across countries despite different accounting standards and can collect and analyze market trading data down to seconds, which then can be packaged as information products to sell to investors.

In this paper we seek to understand how costly information acquisition affects markets for sovereign bonds and default risk. To do so, we construct a model in which the sovereign's default and borrowing decisions as well as the lenders' receipt of payoff-relevant information are jointly endogenous: Lenders always observe some public states, such as output and debt levels, but cannot directly observe other potentially payoff-relevant states when making investment decisions, such as the recovery rate in the event of default. Information regarding

¹The sample period for this database is 2008-2016.

these sorts of shocks can only be acquired at a cost.

In any market-based model of costly information acquisition, one encounters the dilemma highlighted by [Grossman \(1976\)](#), which is that market prices tend to reveal too much information and thus kill incentives to acquire information in the first place. We circumnavigate this issue by separating the information acquisition decision from market participation, much like [Angeletos and Werning \(2006\)](#). An independent contractor/forecaster interested only in the integrity of its forecast such as the credit rating agencies in [Manso \(2013\)](#) or [Holden et al. \(2018\)](#) conducts the information acquisition. As market participants, lenders pay a small fee to gain access to the information that is obtained by the forecaster. The usefulness of the information depends on the acquisition efforts of the forecaster in that state.

Real world analogues of the forecaster might be financial analytics firms, such as Bloomberg or Reuters; alternatively they could be international entities such as the IMF or the World Bank, or credit rating agencies such as Moody's or S&P. Our calibration strategy reflects this market framework. We also avoid emergent signaling games by assuming that the sovereign does not have any informational advantage over lenders at the time of bond issuance and thus cannot signal this information through bond supply.

Costly information acquisition generates a nonlinear dependence of lender knowledge regarding unobserved states on those that are publicly observed. For instance, when debt levels are low and output is high, there is little to gain in terms of accurately inferring unobserved shocks since default risk is negligible for most of their realizations. However, for moderately high debt levels and low output, information is more valuable since unobserved shocks may tip the sovereign over to a default event. Intuitively, the forecaster will start acquiring more information at the beginning of a crisis, more carefully studying the borrower and its associated default risk. This will be reflected in more precise information being transmitted to lenders.

To quantify the impact of this mechanism, we calibrate the benchmark model to Russia and select Bloomberg as our empirical counterpart for the forecaster. Bloomberg not only provides investors with information about sovereign borrowers, but also provides a novel

dataset that they call ‘news-heat,’ that we use as a proxy for information acquisition activity. News-heat tracks Bloomberg publications on sovereign borrowers as well as reading and searching activities on Bloomberg terminals.

The model reveals several insights. First, it amplifies² heteroskedasticity in the country risk spread without assuming it in any of the exogenous fundamental processes. Time-variation in macroeconomic volatility is a well-documented empirical fact (Justiniano and Primiceri [2008] or Bloom [2009]) but little has been done as of yet to understand its causes,³ despite the fact that Fernández-Villaverde et al. (2011) show that second-moment fluctuations in the country-risk spread can have substantial first-moment effects on investment and output.

The intuition behind the heteroskedasticity in our model is as follows: During normal times when debt levels are low and output is high, the forecaster has little to gain from information acquisition regarding unobserved shocks since default risk is negligible for most of their realizations. Consequently, lenders receive little to no accurate information regarding these shocks. They assume them to be at their mean when pricing default risk, which implies that bond yields do not respond to their realizations and spread volatility is lower. However, during periods with high debt levels and low output, i.e., crises, the forecaster more carefully studies the borrower and its associated default risk since unobserved shocks may substantially affect default risk. Hence, lenders acquire additional information about these shocks, which then become priced. This implies that bond yields *do respond* to realizations of unobserved shocks during crisis times, which increases spread volatility.

We propose a model-free metric of heteroskedasticity in the country risk spread that we call the *Crisis Volatility Ratio* (CVR) and use it to demonstrate the efficacy of our model against alternative models. The CVR has a simple construction: It is the sample average

²de Ferra and Mallucci (2022) find that sovereign debt models generate some heteroskedasticity naturally as the elasticity of the bond price schedule increases during debt crises.

³Some notable recent exceptions are Seoane (2019) and Johri et al. (2022), but these papers explain time-varying volatility in the country risk spread by assuming exogenous time-varying volatility in fundamentals. Sedlacek (2020) provides an alternative solution, but it generates time-varying cross-sectional dispersion among firms. Chari and Kehoe (2003) also show that investor herding behavior can increase uncertainty during crises.

of the ratios of sample volatilities surrounding precisely defined ‘crisis’ events. It is a scalar measure of how much more volatile a country becomes on impact in the aftermath of a crisis event. If the underlying process features no heteroskedasticity, e.g., an AR(1), the CVR will approach unity as the sample size grows. We show that Russia featured a CVR of 2.67 in the years following the resolution of its 1998 default, which is within the typical range of an emerging market in a longer time horizon (Table 3). Our model brings this moment significantly closer to the data ($CVR = 2.70$) than an alternate calibration without state-contingent information flows⁴ ($CVR = 2.18$) or even flexible reduced-form models such as an AR-ARCH-M ($CVR = 1.51$).⁵

Another insight revealed by our model regards the dynamics of risk premium. In standard default models, the spread on a bond can be decomposed into two components: Default, dilution, or recovery risk and a risk premium for that risk. The latter is affected not only by investors’ degree of risk aversion, but also by the conditional distribution of payoff-relevant shocks. In our model, information acquisition reduces the variance of this conditional distribution from the perspective of the investor. Consequently, it exerts downward pressure on the risk premium.

This novel channel alters the relative composition of default risk and the risk premium in a couple of ways. First, as information costs fall, so too does the risk premium as investors are effectively exposed to less risk. Second, during crises the risk premium share of the spread decreases mildly as information flows rise to offset risk in the benchmark model, whereas it increases mildly in a re-calibration with no endogenous information flows.

Our model offers a natural framework to consider the impact of transparency policy. We interpret greater transparency here as a reduction in the information costs. We find that transparency works as a double-edged sword on sovereign utility. On the negative side, it increases price volatility as information is acquired and priced more often. This exposes the

⁴CVR values above unity in the no-information model corroborate the finding of [de Ferra and Mallucci \(2022\)](#) that sovereign debt models naturally generate some heteroskedasticity on their own. However, in the Russian data the additional state-contingent volatility generated by our model is necessary to boost the CVR into the empirically relevant range.

⁵Among the GARCH-class models, the data tend to favor the AR-ARCH-M, which is why we contrast our model to this.

104 risk-averse sovereign to additional risk in its budget set and causes it to default more often,
105 which works to hurt the country. At the same time, though, the sovereign benefits from
106 transparency due to lower risk premia. These different forces are at odds with each other in
107 the benchmark model and the result is a welfare trajectory that is fairly flat overall but in
108 which the country’s would-be desire to obscure information exhibits state-contingencies.

109 Finally, we use Bloomberg news-heat data to empirically validate the predictions of our
110 model regarding sovereign spread heteroskedasticity. The analysis here is reduced-form but
111 also broader, incorporating 28 countries over 2008-2016 rather than one. Using a com-
112 bined panel dataset of EMBI and news-heat, we conduct regression analysis to show that
113 increased information flows are associated with greater spread levels and spread volatility in
114 the sovereign bond market. The effect is state-contingent and is only statistically significant
115 during crises, which accords with the predictions of our model.

116 **1.1. Contributions and Related Literature**

117 Our paper contributes to the sovereign debt and asset pricing literature in three dimen-
118 sions. First, our paper studies the quantitative impact of information friction on asset pricing
119 and sovereign welfare dynamics. There has been work done in stylized theoretical environ-
120 ments but not much in standard quantitative models. We are able to introduce information
121 friction in a tractable way by calibrating information costs using the Bloomberg investor-
122 attention measurement and by shutting down signaling games among investors themselves
123 as well as between investors and the borrower. Second, we provide a micro-foundation for
124 time-variation in volatility in the country-risk spread. Third, our paper empirically mea-
125 sures investors’ attention to sovereigns and provides support to our model’s predictions on
126 asset pricing dynamics for a broad set of countries. Existing work concentrates on investors’
127 attention to domestic firms and their stocks and not to foreign sovereign borrowers and their
128 bonds.

129 Our model’s focus on relations between a single sovereign borrower and its lenders over
130 time and the implications for the ergodic price distribution distinguishes our analysis from the
131 related work of [Cole et al. \(2022\)](#). These authors also explore a model of costly information

acquisition in sovereign debt markets, but their focus is static. They highlight the potential for this channel to cause contagion effects across many countries and generate multiplicity. [Angeletos and Werning \(2006\)](#) and [Carlson and Hale \(2006\)](#) also explore how market-based information acquisition or rating agencies affect equilibrium multiplicity or uniqueness in variations on the canonical model of [Morris and Shin \(1998\)](#). [Durdu et al. \(2013\)](#) explore the impact of news shocks in a similar model. Recently, [Bassetto and Galli \(2019\)](#) also study the role of information on sovereign bond pricing in a two-period Bayesian trading game, focusing on implications for inflation risk.

Relatedly, it is worth distinguishing our paper from the vast literature that studies sovereign defaults and information asymmetry. For instance, [Cole and Kehoe \(1998\)](#), [Sandleris \(2008\)](#), [Catao et al. \(2009\)](#), [Wittenberg-Moerman \(2010\)](#), [Hellwig et al. \(2014\)](#), [Pouzo and Presno \(2016\)](#), [Croitorov \(2016\)](#), [Mihm \(2016\)](#), and [Perez \(2017\)](#) among others have all shown that information asymmetries and uncertainties are key to explaining various features of sovereign bond markets, though none have considered the consequences of allowing information to be gathered at a cost. Another important distinction is that, although our model and these other papers all assume incomplete information for investors, our model mechanism does not require any information asymmetry between the borrower and the investors or any information asymmetry among investors. The model focuses on investors' costly information acquisition behavior regardless of reputation concerns.

[de Ferra and Mallucci \(2022\)](#) recently show that [Arellano \(2008\)](#) in its unaltered form generates endogenous heteroskedasticity in spreads that align with the data for its calibration. The mechanisms behind this, namely greater bond price elasticity at higher debt levels, is also at work in our model, as is evidenced by the model without information flows generating CVRs that indicate heteroskedasticity. However, we find that the additional inclusion of costly information acquisition is required to generate CVRs in line with our (Russian) data. Further, our model has novel implications for risk premium dynamics and transparency policy that cannot be discussed in the standard [Arellano \(2008\)](#) framework.

This paper is also connected to a growing literature on corporate finance, stock returns,

and investor information acquisition. [Dang et al. \(2015\)](#) and [Babenko and Mao \(2018\)](#) consider optimal security design problems in the financing of a risky investment with information acquisition. [Pagano and Volpin \(2012\)](#) show that issuers of asset-backed securities may choose to release coarse information to enhance primary market liquidity, even if it reduces secondary market liquidity. [Barber and Odean \(2008\)](#), [Da et al. \(2011\)](#), [Ben-Rephael et al. \(2017\)](#) show empirically that investor attention predicts stock returns and [Cziraki et al. \(2021\)](#) show that the geographic distribution of attention matters for stock returns. Most similar to our work are [Vlastakis and Markellos \(2012\)](#), [Andrei and Hasler \(2015\)](#), and [Dimpfl and Jank \(2016\)](#) who show that an increase in investor attention corresponds to an increase in stock-return volatility.

Our empirical analysis is closely related to the recent work by [Bi and Traum \(2019\)](#). They use data about fiscal information from U.S. newspapers in the 1840s and find that state government bond prices were especially sensitive to fiscal news during crisis time, relative to normal time. Their results are consistent with the broad predictions of our model and empirical results.

The remainder of this paper is divided as follows: Section 2 describes the model; Section 3 discusses the data and quantitative implementation of the model; Section 4 demonstrates the model’s key results; Section 5 tests the empirical predictions of the model in a broader dataset; and Section 6 concludes.

2. Model

We consider a small open economy model of endogenous sovereign default in the vein of [Eaton and Gersovitz \(1981\)](#). This is in part for tractability and in part to demonstrate our model’s applicability and compare results to the recent, expanding quantitative literature, e.g., [Aguiar and Gopinath \(2006\)](#), [Arellano \(2008\)](#), [Hatchondo and Martinez \(2009\)](#), or [Mendoza and Yue \(2012\)](#). There is a sovereign borrower who issues long-term non-state-contingent debt to a unit mass of foreign lenders. This borrower lacks the ability to commit to repay this debt in subsequent periods and will default if it is optimal to do so ex post.

The borrower also lacks the ability to commit to future borrowing behavior.

For clarity, we distinguish a random variable from its realization by placing a tilde over the former.

2.1. Shocks

There are two fundamental shocks in this model. The first is a transitory shock to the sovereign's endowment Y_t that follows a Markov process with transition density $f_t(Y_{t+1}|Y_t)$. In particular, we assume that log-endowment follows an AR process, $\log Y_t = \rho_y \log Y_{t-1} + \sigma_y \epsilon_t$, where ϵ_t is a standard normal.⁶ The endowment and its shocks are publicly observed by everyone.

The second shock in the model is an i.i.d recovery rate on defaulted debt, m_t .⁷ m_{t+1} is not publicly observed by anyone when it is realized in the middle of period t . However, we will assume that a professional forecaster may pay a cost to observe an imperfect signal of it, x_t , at this time. This signal (and its correlative structure with m_{t+1}) then becomes public knowledge at the time the debt is priced. m_t is assumed to be logit-normally distributed, which allows for it to be bounded on $[0, 1]$ while maintaining a jointly normal information structure with the correlate, x_t . We also assume that once the sovereign is in a default event, the value of m stays constant throughout the event until the default regime is over.

2.2. Timing

The timing of events is as follows: Period t begins with the realization of Y_t , following which the sovereign makes a default decision with knowledge of the m_t realization. Conditional on repayment, it then chooses a level of debt issuance B_{t+1} to maximize its expected utility prior to the realization of m_{t+1} .

Next, a professional forecaster, who observes the public states Y_t and B_{t+1} , chooses the accuracy with which he acquires information about m_{t+1} given some information cost. He

⁶Note that our endowment structure features transitory shocks in the vein of [Arellano \(2008\)](#). This is not crucial to the novel mechanism; the intuition goes through with permanent shocks to income following [Aguar and Gopinath \(2006\)](#) as well.

⁷Since default events are rare in both data and our model, most of the reset recovery rates each quarter do not show in the data nor matter to the sovereign borrow or the investors in the model. What matters are those few recovery rates that are actually used during the rare default events. Hence, it is difficult to estimate the recovery rate process for every quarter and assuming the rate being i.i.d keeps the model calibration simple.

designs a signal of the unobserved shock, x_t , and can pay a cost to increase its accuracy.

Following the information acquisition decision, m_{t+1} and x_t are jointly realized in the middle of period t . The market coordinates on the signal: Competitive lenders, knowing both the signal and its accuracy, then decide bond demand. The sovereign then determines an issuance price that clears the bond market and period t ends.

Notice that we assume that the sovereign cannot change its bond supply following the realization of m_{t+1} .⁸ This allows us to focus on the role of information acquisition and avoid the complicated and, for our purposes, unnecessary signaling game that would ensue.

2.3. Sovereign Borrower

As is standard in the literature, we use a recursive, Markov-Perfect specification with limited commitment on the part of the sovereign. At the beginning of each period, the sovereign compares the value of repaying debt, $V_{R,t}$, with that of default, $V_{D,t}$, and chooses the option that provides a greater value:

$$V_t(Y_t, B_t, m_t) = \max\{V_{R,t}(Y_t, B_t), V_{D,t}(Y_t, B_t, m_t)\}$$

The sovereign has standard time-separable concave preferences over consumption and is a monopolist in his own debt market. Given the timing assumption, we can express the value of repayment at the beginning of period t as follows:

$$V_{R,t}(Y_t, B_t) = \max_{B_{t+1} \in \mathcal{B}_t} \mathbb{E}_{\tilde{x}_t} \left[u(C_t(\tilde{x}_t)) + \beta \mathbb{E}_{\tilde{m}_{t+1}, \tilde{Y}_{t+1} | Y_t, \tilde{x}_t} \left[V_{t+1}(\tilde{Y}_{t+1}, B_{t+1}, \tilde{m}_{t+1}) \right] \right] \quad (1)$$

$$\text{subject to } C_t(x_t) = Y_t - [\lambda + z(1 - \lambda)]B_t + q_t(B_{t+1} | Y_t, x_t)[B_{t+1} - (1 - \lambda)B_t]$$

$$\text{and } q_t(B_{t+1} | Y_t, \bar{x}) \geq \bar{q} \text{ if } B_{t+1} > (1 - \lambda)B_t$$

The long-term bond matures with probability λ , following [Chatterjee and Eyigungor \(2012\)](#). For the bond that does not mature, each unit pays out a coupon amount of z . The determination of the issuance price schedule, $q_t(B_{t+1} | Y_t, x_t)$, will be discussed in the market clearing section below. We impose the additional restriction suggested by [Hatchondo et al. \(2016\)](#), which places a lower bound on prices⁹ when countries are issuing debt. As in their

⁸We do not specify whether sovereign gets to know m_{t+1} before or after the lenders do. It does not matter, since the sovereign decides its bond supply before m_{t+1} realizes and cannot change its issuance decision in either case.

⁹Here, it is actually the most likely price, since prices are not realized at issuance.

model, this prevents the country from substantially diluting legacy investors in a gambit that ensures a default probability near one in the next period. It does not, however, affect on-equilibrium dynamics in any significant way provided \bar{q} is low enough.

When a default happens in period t , the sovereign ceases servicing the debt, is excluded from credit markets, and faces weakly positive, additive output losses $\psi(Y_t) = \max\{\theta_0 Y_t + \theta_1 Y_t^2, 0\}$. These costs could be interpreted as the usual consequences of tightening credit conditions, a disruption of trade credit, or a banking slump (Mendoza and Yue [2012] or Sosa-Padilla [2018]).

Our model also features recovery on defaulted bonds, as in Hatchondo et al. (2016). When a default happens, a debt swap is proposed with Poisson probability ϕ and the sovereign can choose to accept it to return to credit markets, or reject it to stay in financial autarky and wait for another proposal. The size of the recovery rate in these proposals is the source of unobserved uncertainty in the period before default, i.e., m_t . After default, m_t is assumed to be constant until the sovereign accepts a proposal and returns to the credit markets. Under these assumptions, the value of default can be expressed recursively as follows:

$$V_{D,t}(Y_t, B_t, m_t) = u(C_t) + \beta \mathbb{E}_{\tilde{Y}_{t+1}|Y_t} \left[\phi V_{t+1}(\tilde{Y}_{t+1}, m_t B_t, m_t) + (1 - \phi) V_{D,t+1}(\tilde{Y}_{t+1}, B_t, m_t) \right]$$

subject to $C_t = Y_t - \psi(Y_t)$ (2)

Notice that the sovereign's choosing to accept or reject a debt swap proposal is embedded in the term $V_{t+1}(\tilde{Y}_{t+1}, m_t B_t, m_t)$. In particular, it may reject a proposal if its current endowment state makes it more valuable to remain in the default regime. Moreover, every time the sovereign rejects a proposal, the next proposal will further reduce the debt to be repaid by the same haircut rate. Hence, both the accumulated haircut by the time the sovereign accepts a proposal and the number of periods of continuous financial exclusion are endogenous and depend on how many times the sovereign rejects a proposal.

It is worth noting that the repayment value does not take m_t as an argument since the recovery rate m_t is irrelevant should the sovereign choose to repay because it is i.i.d. On the other hand, $V_{D,t}$ does take m_t as an argument because it determines the size of the haircut when it is eventually proposed. V_t is a function of both $V_{R,t}$ and $V_{D,t}$ and hence it takes m_t

as an argument.

We define the sovereign’s default decision with a binary operator:

$$d_t(Y_t, B_t, m_t) = \mathbf{1}\{V_{R,t}(Y_t, B_t) < V_{D,t}(Y_t, B_t, m_t)\}$$

2.4. Forecaster

There is an inherent difficulty associated with market-based information acquisition problems: The price tends to convey too much information. Perfect Bayesian investors can infer all relevant information from market prices, which gives them no incentive to acquire information in the first place ([Grossman \[1976\]](#), [Kyle \[1985\]](#), or [Dow and Gorton \[2006\]](#)). We circumvent this problem by designing the market to operate with complete rationality and transparency on a signal of the true hidden information.¹⁰ No additional information regarding payoff-relevant states can be gleaned from the price besides what participants already know.

In particular, we separate the information acquisition decision from bond investment, much like [Angeletos and Werning \(2006\)](#). We assume that all lenders are fully rational, but that each acquires information by employing the same contractor, whom we call the forecaster. [Veldkamp \(2011\)](#) argues that information is a commodity that is difficult to obtain but essentially costless to disseminate. Our market set-up reflects this feature of information production by allocating the task to a single specialist. Once the information is produced, it is transmitted to all market participants. Real-world analogues of the forecaster would be financial media and analytics firms such as Bloomberg or Reuters. Alternatively, they could be interpreted as financial news or media outlets such as the Wall Street Journal or the Financial Times, credit rating agencies such as Moody’s or S&P, or supranational public institutions such as the International Monetary Fund.

The forecaster has a technology capable of gathering information regarding the unobserved shock, m_{t+1} , at a per-unit cost κ . He sells his services to lenders as an independent contractor for a small fee, $l_t \geq 0$. A subscription fee for such a service is not unrealistic. For instance,

¹⁰The other popular option is to add unseen noise to the aggregate supply, e.g., [Grossman and Stiglitz \(1980\)](#). In our model, however, supply is determined by the optimal behavior of the sovereign. Thus, there is little plausible room for such noise.

one pays a subscription fee to access IMF's International Financial Statistics data or a Bloomberg terminal. We also assume for simplicity that lenders must pay this subscription fee to have access to the sovereign bond market, such that all lenders in this market have access to a forecaster-provided signal of the unobserved shock.

The forecaster is interested in the integrity of its forecasts, much like the rating agencies in [Holden et al. \(2018\)](#) or [Manso \(2013\)](#). It actively weighs this objective against information acquisition costs. In each period it produces a signal, x_t , of the next period's unobserved shock, m_{t+1} . The signal and the logit of the unobserved true state are jointly normal, and the information contained in this signal is reflected in $\rho_{mx,t} = \text{corr}(x_t, m_{t+1}) \in [0, 1]$, which is the forecaster's choice.¹¹ That is, the forecaster can modify the signal to make it more or less informative about m_{t+1} : More informative signals will feature a larger $\rho_{mx,t}$. For this reason we will call $\rho_{mx,t}$ the *accuracy* or *precision* of the signal.¹² The forecaster uses this information to publish a forecast (distribution) over all future states, observed and unobserved: $\hat{f}_t(Y_{t+1}, m_{t+1} | Y_t, x_t) = f_t(Y_{t+1} | Y_t) g_{\rho_{mx,t}}(m_{t+1} | x_t)$.

Since it is the investors who pay the contractor, we further assume that the forecast with whose integrity the forecaster is concerned is the return profile of the investors. As such, the forecaster designs the signal, x_t , to minimize the uncertainty associated with their ex-post returns.

In our benchmark, we assume m_{t+1} and x_t to be orthogonal to observed states Y_t , but our framework is flexible enough to allow for some correlation with no change in the mechanism. The forecaster would simply acquire the residual information that is not conveyed through observed states.

The information required to obtain a signal is given by a time-invariant function, $I(\rho_{mx,t})$, which is increasing in signal accuracy. The per-unit cost of information is a constant κ . In the benchmark, we assume that $I(\cdot)$ is the reduction in entropy in m_{t+1} that comes from

¹¹Our restriction to signals with positive correlation is without loss of generality, since negatively correlated signals have the same information content.

¹²This information structure is isomorphic to a Gaussian signal-noise model in which the forecaster chooses the variance in the noise. We prefer our specification to this, though, since it features a closed domain, i.e., an infinitely noisy signal would arise with some regularity along the equilibrium path.

knowledge of x_t , but our results do not hinge on this functional form.¹³ Any increasing function would work.

We formulate the forecaster’s information acquisition problem as below, given Y_t and B_{t+1} :

$$\begin{aligned} \min_{\rho_{mx,t} \in [0,1]} \quad & \mathbb{E}_{\tilde{x}_t} \mathbb{E}_{\tilde{m}_{t+1}, \tilde{x}_{t+1}, \tilde{Y}_{t+1} | \tilde{x}_t, Y_t} \left[R_{t+1}(\tilde{Y}_{t+1}, B_{t+1}, \tilde{m}_{t+1}, \tilde{x}_{t+1}) - \bar{R}_{t+1} \right]^2 + \kappa I(\rho_{mx,t}) \quad (3) \\ \text{subject to} \quad & \bar{R}_{t+1} = \mathbb{E}_{\tilde{m}_{t+1}, \tilde{x}_{t+1}, \tilde{Y}_{t+1} | Y_t} \left[R_{t+1}(\tilde{Y}_{t+1}, B_{t+1}, \tilde{m}_{t+1}, \tilde{x}_{t+1}) \right] \end{aligned}$$

where R_{t+1} are ex-post investor returns, which are defined in Section 2.5.¹⁴ To see the benefit of information acquisition, notice that the variance of the interior expectation is decreasing in $\rho_{mx,t}$. Consequently, the variance in the forecaster’s return forecast can be reduced if he is willing to undergo costly information acquisition.

But these benefits are state-contingent. When Y_t and B_{t+1} indicate a greater risk of default, and thus return risk as a result of uncertain recovery, acquisition of more accurate information will prove a valuable endeavor, since m_{t+1} matters for the ex-post return. When these publicly known states instead indicate little to no default risk, and thus little to no return risk, the forecaster can save on information costs and provide imprecise or even orthogonal signals because m_{t+1} is adding little to no variance to the forecast.

2.5. Foreign Lenders

There is a unit mass of risk-averse foreign lenders who invest in risky sovereign debt. These lenders act competitively, similarly to Lizarazo (2013) or Aguiar et al. (2016). Lenders arrive in overlapping generations and each lives for two periods. Each lender is endowed with wealth, w_t , and pays the contractor fee, l_t , to gain access to the forecaster’s signal, x_t . Then, they solve a portfolio allocation problem to decide how much to invest in risky sovereign debt and how much to invest in a risk-free asset yielding a return, r .

Overlapping lenders can arrive in one of two states of the world: Sovereign inclusion in

¹³This notion of information was developed primarily by Shannon (1958) and applied to economics by Sims (2003, 2006).

¹⁴Since return risk is the only risk investors are exposed to, one could interpret the ‘joint agent’ of forecaster and investors as a single rationally inattentive agent that is restricted to a Gaussian signal structure and maximizes a monotone transformation of the second-order approximation of the utility function when making information processing/acquisition decisions. Such second-order approximations are common in the applied rational inattention literature ,e.g., Mackowiak and Wiederholt (2009).

capital markets or sovereign default/exclusion. In states of inclusion, new lenders purchase debt both from the sovereign and the legacy lenders who held bonds that did not mature, i.e., both primary and secondary markets are active. In states of default/exclusion, legacy lenders alone supply debt to be purchased and thus only secondary markets are active.

2.5.1. Demand During Inclusion

Given the above setup, investor i takes the bond issuance price, q_t , as given and solves the following problem, knowing public states Y_t and B_{t+1} as well as the signal x_t and its accuracy $\rho_{mx,t} = \rho_t(Y_t, B_{t+1})$:

$$\max_{b_{i,t+1}} \mathbb{E}_{\tilde{Y}_{t+1}, \tilde{m}_{t+1}, \tilde{x}_{t+1} | Y_t, x_t} \left[\frac{\tilde{c}_{i,t+1}^{1-\gamma_L}}{1-\gamma_L} \right] \quad (4)$$

subject to $c_{i,t+1} = [w_t - l_t - b_{i,t+1}q_t](1+r) + b_{i,t+1}R_{t+1}(Y_{t+1}, B_{t+1}, m_{t+1}, x_{t+1})$

where $R_{t+1}(Y_{t+1}, B_{t+1}, m_{t+1}, x_{t+1}) = d_{t+1}(Y_{t+1}, B_{t+1}, m_{t+1})q_{D,t+1}(Y_{t+1}, B_{t+1}, m_{t+1})$

$+ [1 - d_{t+1}(Y_{t+1}, B_{t+1}, m_{t+1})]\{\lambda + (1-\lambda)[z + q_{t+1}(A_{t+1}(Y_{t+1}, B_{t+1})|Y_{t+1}, x_{t+1})]\}$

where A_{t+1} is the issuance policy in period $t+1$ and $q_{D,t+1}(Y_{t+1}, B_{t+1}, m_{t+1})$ is the price in the secondary market of a bond that has been defaulted on. Notice there is no Bayesian extraction problem to be undertaken as in [Lucas \(1972\)](#), [Grossman \(1976\)](#), or [Bassetto and Galli \(2019\)](#), since the forecaster has coordinated market expectations on its noisy signal.

We denote aggregate bond demand in non-defaulting periods by:

$$B_{D,t+1}(Y_t, x_t, B_{t+1}, q_t) \equiv \int_0^1 b_{i,t+1}^*(Y_t, x_t, B_{t+1}, q_t) di.$$

Though we use the i -index to denote individual investors, there is no heterogeneity among them, so the indexing will be irrelevant to equilibrium dynamics.

2.5.2. Demand During Exclusion

A lender who purchases a bond during a period of sovereign exclusion also faces uncertainty. One of three things can happen: (1) Next period there is no proposed swap and the creditor sells all her holdings on the secondary market, i.e., $b_{i,t}q_{D,t+1}$; (2) Next period there is a proposed debt swap and the sovereign accepts, in which case the creditor receives payment on a fraction of the bond, i.e., $m_t b_{i,t}$; and (3) next period there is a proposed debt swap and the sovereign rejects, in which case the secondary bond supply shrinks by m_t and

the creditor sells her reduced holdings at the secondary market price, i.e., $m_t b_{i,t} q_{D,t+1}$.

Given our recovery set-up spelled out above, secondary bond demand at a given price, $q_{D,t}$, is determined as follows:

$$\max_{b_{i,t}} \mathbb{E}_{\tilde{Y}_{t+1}, \tilde{x}_{t+1} | Y_t, m_t} \left[\frac{\tilde{c}_{i,t+1}^{1-\gamma_L}}{1-\gamma_L} \right] \quad (5)$$

subject to $c_{i,t+1} = (w_t - l_t - b_{i,t} q_{D,t})(1+r) + b_{i,t} R_{D,t+1}(Y_{t+1}, B_t, m_t, x_{t+1})$

where $R_{D,t+1}(Y_{t+1}, B_t, m_t, x_{t+1}) = (1-\phi)q_{D,t+1}(Y_{t+1}, B_t, m_t)$

$+ \phi [1 - d_{t+1}(Y_{t+1}, m_t B_t, m_t)] \{ \lambda + (1-\lambda)[z + q_{t+1}(A_{t+1}(Y_{t+1}, B_{t+1}) | Y_{t+1}, x_{t+1})] \} m_t$

$+ \phi d_{t+1}(Y_{t+1}, m_t B_t, m_t) q_{D,t+1}(Y_{t+1}, m_t B_t, m_t) m_t$

Notice that in this market m_t is constant and already known, with public states Y_t and B_{t+1} .

Despite this, we assume that investors' subscription and access to the forecaster stand and thus still pay the contractor fee l_t .

2.6. Market Clearing

Once the information structure is chosen by the forecaster, the signal is realized and distributed to all lenders, who then enter a competitive market with a common information set. The sovereign issues its predetermined debt stock, B_{t+1} at the highest possible price. Market clearing requires that $B_{D,t+1} = B_{t+1}$ in states of inclusion. This yields a pricing schedule identical in structure to that in [Aguiar et al. \(2016\)](#) but with the inclusion of the signal realization as an additional state.

The forecaster plays no role in the exclusion states since they can mitigate no risk for buyers or sellers there. Again, lenders will be representative and the market price, $q_{D,t}$ will adjust until $B_{D,t} = B_t$, where $B_{D,t}$ is given by the solution to Equation 5.

2.7. Equilibrium Definition

Definition 1. A Markov Perfect Equilibrium is a set of functions,

$\{V_t(Y_t, B_t, m_t), V_{R,t}(Y_t, B_t), A_t(Y_t, B_t), V_{D,t}(Y_t, B_t, m_t), \rho_t(Y_t, B_{t+1}), q_t(B_{t+1} | Y_t, x_t), q_{D,t}(Y_t, B_t, m_t)\}_{t=0}^{\infty}$

such that (1) $V_{R,t}(Y_t, B_t)$ and $V_{D,t}(Y_t, B_t, m_t)$ solve Recursions 1 and 2 and imply the policy

$B_{t+1} = A_t(Y_t, B_t)$ and $V_t(Y_t, B_t, m_t) = \max\{V_{R,t}(Y_t, B_t), V_{D,t}(Y_t, B_t, m_t)\}$; (2) $\rho_t(Y_t, B_{t+1})$

solves Problem 3; (3) $q_t(B_{t+1}|Y_t, x_t)$ ensures that the market clears in states of non-exclusion, where bond demand is derived from Problem 4; and (4) $q_{D,t}(m_t, Y_t, B_t)$ ensures that the secondary market clears in states of exclusion, where demand is derived from Problem 5.

3. Calibration

To determine the impact that costly information acquisition has on the pricing of sovereign risk, we calibrate the model to match a set of empirical moments from twenty-first century Russian quarterly data. This period follows the resolution of the 1998 default but includes a large, salient crisis in late 2014 and 2015. The intuition, however, is general enough that we could perform the exercise for other countries.

While the state space is not overly large, being at most 3-dimensional, the model requires the accurate computation of many multidimensional and highly computationally expensive expectations, especially in the forecaster’s problem. Traditional methods prove insufficient for this task even with extensive parallelization and high-caliber computing resources. Thus, we solve the model using a specially tailored machine learning algorithm derived from the procedure described by Scheidigger and Bilonis (2019). Details regarding the solution of the model can be found in Appendix A, and the algorithm there contained is suitable not only for our particular model but for a wide range of sovereign debt and structural macroeconomic models.

We draw data from three primary sources: First is the JP Morgan Emerging Market Bond Index (EMBI) database taken from Datastream; second is the World Bank International Debt Statistics database; and third is Bloomberg’s news-heat database.

3.1. Information Cost Identification

First and foremost, to find a proper cost value per unit information, κ , we match the variability of information acquisition in the model and in the data. We find a value for κ that matches, in the model and the data, the fraction of periods in which intense attention is paid to the borrower country, where intense attention is defined as information flows greater than the midpoint (i.e., half of the maximum attention level that is ever paid to a country

during the sample period). As information becomes infinitely costly, this fraction approaches zero; as it cheapens, this fraction grows roughly monotonically.¹⁵

The model has a direct measure of information acquisition, ρ_{mx} . The literature has proposed many different empirical measures of ‘attention’ or information acquisition ranging from news to trading volume to extreme returns to Google search trends.¹⁶ Given our model set-up, we instead select an empirical entity, Bloomberg, to serve as the forecaster, and invoke their news-heat data as an empirical proxy for information acquisition. Since Bloomberg terminal users are mainly financial professionals who are likely to have both the incentives and financial resources to react to important news, this news-heat dataset can be used as a proxy for investor attention on a specific equity and its underlying company or sovereign.¹⁷

Bloomberg news-heat data come in two types: One measures the daily number of its news stories on companies and sovereigns; the other measures its users’ news reading and news searching activities on Bloomberg terminals.¹⁸ For instance, [Ben-Rephael et al. \(2017\)](#) use Bloomberg news-heat daily max readership data and find significant impact of institutional investors’ attention on their trading behavior and stock price dynamics. To best mimic the structure of the model, we use Bloomberg daily total number of news story publications as our main indicator for investor attention, since it proxies for Bloomberg’s information acquisition efforts.¹⁹ It is similar to [Bi and Traum \(2019\)](#), who use the volume of newspaper articles related to fiscal policy as a measure of investor attention. This publication measure also has better data quality than the news-heat readership data in our case.

The sample period ranges from 3/3/2008 to 3/14/2016 for 61 countries.²⁰ We sum the

¹⁵This fraction would grow monotonically except for the general equilibrium effect that the sovereign may change his behavior in response to more information acquisition, which changes the underlying profile of risk being evaluated by the forecaster.

¹⁶[Barber and Odean \[2008\]](#), [Gervais et al. \[2001\]](#), [Seasholes and Wu \[2007\]](#), or [Da et al. \[2011\]](#).

¹⁷See [Ben-Rephael et al. \(2017\)](#) for a composition of Bloomberg clients’ job titles and industries.

¹⁸Although Bloomberg does not track news-heat on bonds directly, according to Bloomberg one can still measure investors’ attention on issuers by taking the news-heat data corresponding to the primary equity that is underlied by an issuer. We first use Bloomberg’s World Countries Debt Monitor to identify equities that are associated with sovereigns and their debt, and then obtain news-heat data on these equities.

¹⁹In Section 5, we conduct formal econometric exercises on all emerging economies in a matched EMBI/news-heat dataset of 28 countries.

²⁰Historical data are missing for the periods of 8/22/2008–10/19/2008 and from 3/15/2016 onward.

daily publication data on a sovereign over a quarterly frequency and normalize each observation by the total number of publications on all available countries in the entire dataset for that quarter. Consequently, our measure of attention to a sovereign is a quarterly time-series that can be described as a publication share. The fraction of periods with intense attention by this metric is 19% for Russia.

3.2. Other Parameters

To obtain the output process, we estimate via MLE an AR(1) process on band-pass-filtered log dollar-valued real Russian GDP²¹ from 2003-2021 at a quarterly frequency. We use the filter to isolate frequencies ranging from 1.5 to 8 years, which is in the typical range for quarterly macro models using this filter (see [Christiano and Fitzgerald \[2003\]](#)). The MLE estimates that emerge from this procedure are $\rho_y = 0.9212, \sigma_y = 0.0226$, which are quite similar to the values employed by [Arellano \(2008\)](#) and [Chatterjee and Eyigungor \(2012\)](#), which are derived from Argentine data. We endow the sovereign with power utility with a CRRA given by $\gamma = 2$, as is standard in the literature.

We capture empirically relevant recovery dynamics by ensuring that our logit-normal recovery process matches both the mean and volatility of bond recovery data taken from [Asonuma \(2012\)](#), who explores debt renegotiations and settlements for serial defaulters using recovery data from [Benjamin and Wright \(2013\)](#). The mean recovery rate from this sample is 0.652 and volatility of recovery rates is 0.214. A logit-normal generates these two moments when the underlying Gaussian shock has a mean of 0.79287 and a volatility of 1.15429. The density of the estimated recovery shock distribution can be found in Figure 1.

We further assume that the risk-free rate is fixed at 1% quarterly; that the lenders exhibit constant relative risk-aversion preferences with CRRA γ_L ; and that $\phi = 0.083$, which is the estimate used by [Mendoza and Yue \(2012\)](#) for an average duration of 6 years before returning to international bond markets.²² For simplicity, we normalize lender wealth to be, $w_t = 1 + l$,

²¹Output data obtained from St. Louis FRED.

²²We find, as do [Hatchondo et al. \(2016\)](#), that the sovereign takes the first deal proposed to exit autarky with probability near unity.

such that after paying fixed forecaster fees they have a unit mass of wealth to invest. The exact value of l is irrelevant given this normalization and all risk-aversion is driven by the choice of γ_L . The sovereign does not pay the forecaster since Bloomberg is our empirical analogue.

We calibrate the coupon on the bond to be $z = r/(1 - \lambda)$ following [Aguiar et al. \(2016\)](#), since this specification ensures that a risk-free bond has a price of one regardless of maturity. We also set the lower bound on the price during debt issuance to $\bar{q} = 0.7$, following [Hatchondo et al. \(2016\)](#).

Following [Arellano \(2008\)](#), we take our debt moments from the World Bank International Debt Statistics database from 2001-2020. This database provides information on foreign debt service of long-term public and publicly guaranteed debt as well as payments on *all* foreign short-term debt. To compute the effective public debt burden, we assume that the the government is explicitly or implicitly responsible for half of short-term foreign debt payments. Combining this with the data on long-term public debt service and total external debt stocks that average foreign quarterly debt service as a share of the total external debt stock is of the total stock of debt is 6.6%. Given our assumptions on the coupon structure, this implies an average maturity of $\lambda = 5.6\%$ quarterly.

We calibrate the remaining five parameters, $\{\beta, \theta_0, \theta_1, \gamma_L, \kappa\}$, using simulated method of moments (SMM) to jointly match five moments: Average annualized spread, annualized spread volatility, average debt-to-GDP, the average risk premium, and the fraction of quarters with intense attention.²³

The average annualized spread and the spread volatility are taken from the JP Morgan EMBI spread for Russia for 2001-2018 and are 3.1% and 2.2% respectively. To compute the average risk premium, we follow [Longstaff et al. \(2011\)](#), who decompose the spread into default risk and a risk premium as follows: After estimating their model with a risk-averse pricing kernel, they price the exact same default risk using a risk-neutral pricing kernel and

²³The model is at a quarterly frequency; during calibration, model moments are annualized to match certain data moments at an annual frequency.

back out the implied spread, and find that about 1/3 of the spread is a risk premium. We repeat this exercise in our model, computing the average spread demanded by a hypothetical risk-neutral lender, and target the ratio of this default risk against our benchmark average spread, which is 2/3.

To derive the foreign-debt-to-GDP target, we combine our maturity and debt service estimates with the World Bank figures on foreign debt service as a share of GDP, which is 4.2%. This delivers an average foreign-debt-to-GDP target of 64.0%.

The benchmark parameters are given in Table 1. The fit to targeted moments is not perfect²⁴, but it is quite close. Each parameter in Table 1 is primarily identified by its corresponding target moment, though there are significant and non-negligible cross-partial effects. We present in Table 1 both a calibration for the benchmark model and a “no-information” calibration in which we set information costs to infinite and match all the targeted moments except the attention fraction. This alternate calibration will be useful in our discussion of the results.

4. Results

4.1. Typical Crises/Defaults

The acquisition of more information during crises has a number of results and implications. Before we exposit the properties that arise from this, it is worth verifying that our model exhibits standard behavior along the dimensions of output and indebtedness. We do this by observing policy and pricing functions from the model as well as comparing model-derived and empirical moments, which can be found in Table 2. From this point on, when we refer to the “standard” model, we are referring both to [Arellano \(2008\)](#) and its extension to long-maturity debt, [Chatterjee and Eyigungor \(2012\)](#).

As in the standard model, there is positive curvature in the default costs, meaning that it is relatively more expensive to default in good times than in bad. Translating the calibrated values of θ_0 and θ_1 into something more understandable, in the benchmark economy the

²⁴For general non-linear systems such as this, we are not guaranteed a perfect fit exists.

sovereign faces no default cost when output is below about $y_{thresh} = 0.9$ and faces a proportional output cost of about 22.5% when output is three unconditional standard deviations above steady state of $y_t = 1.0$. This is a bit more curvature than is found by Chatterjee and Eyigungor (2012) and a bit less than is found by Arellano (2008).

Because of this curvature in the default costs, there is a tension between consumption smoothing incentives and borrowing costs. During a recession, the country would like to borrow to smooth consumption in the face of lower output. However, because output is persistent, low future output indicates low default costs and thus higher default probabilities, which raises borrowing costs and dissuades borrowing. This dynamic is evident in the pricing functions observed in Figure 2b and implies countercyclicality in spreads (output correlation = $-.55$). Spread countercyclicality is a salient and non-targeted feature of the data as well and in magnitudes that roughly match the model (output correlation = $-.52$).

The tension between consumption-smoothing motives and countercyclical spreads is evident in the policy function in Figure 2a. We observe here that consumption-smoothing motives dominate the country's decision for low to intermediate debt levels, i.e., between $B_t = 0.1$ and $B_t = 0.5$, as the country borrows more in recessions than booms. However, at higher debt levels near the ergodic mean, the price effect dominates and the country borrows more during booms and recessions as the spreads are lower. This tension also implies trade balances that are near acyclic (output correlation = $-.03$), which is also a feature of the data (output correlation = $.12$).

The fact that the country tends to borrow procyclically near the ergodic mean has consequences that are well-known in the literature. For instance, the consumption-output volatility ratio tends to be large relative to developed economies. Table 2 reveals that consumption-output volatility ratio is about 1.2 in the model. Empirically, this ratio is about 0.98. These are both significantly larger than what Restrepo-Echavarria (2014) finds developed economies, which exhibit consumption-output volatility ratios around .81. Domestic expenditures are also strongly procyclical in the model and data, with output correlations of 0.87 and 0.99 respectively.

Procyclical borrowing behavior also leads to default dynamics resembling standard models in the literature. In the data as well as standard models defaults are typically rare and relatively unforeseen before they occur. This can be seen concretely in Table 2, which reveals that the average probability of a default event occurring as perceived by investors the quarter before a default is only about 1.36%. This is more than double than the unconditional quarterly average of .6%, but remains quite unlikely. This suggests that the vast majority of defaults come as nasty and unexpected shocks.

To explore such a typical default in the benchmark model, we first simulate the model for a long time (half a million periods) and locate all default events; then we restrict attention to defaults that were unforeseen more than year before the crisis²⁵; finally, from this restricted set, we choose the default event associated with the highest likelihood of exogenous shocks in the years preceeding the year in which the default occurred. The result of this exercise can be seen in Figure 3.

Figure 3 reveals that such defaults occur just as they would in standard models such as Arellano (2008). In particular, such defaults tend to occur when a country experiences a prolonged output boom in the four or so years prior to the default. The country borrows into this boom, increasing his indebtedness as time goes by. Spreads fall gently during this boom, reflecting falling default costs and the increased probability of repayment.

Before default occurs, though, the country experiences a significant contraction in output in the year leading up to the default event itself. This drives up spreads significantly, more than tripling them. The country attempts to delever to reduce spreads, but the going is slow because consumption smoothing motives work against this price motive. Ultimately a combination of bad output and recovery shocks causes a default before the country can get out of trouble.

The only model moments in Table 2 we have not discussed that are markedly different than their empirical counterparts are the average levels of domestic expenditure and the

²⁵This is done by restricting attention to defaults precipitated little to no information acquisition in the three years prior to the year in which the default took place.

trade balance. Together, these sum to output both in the model and in the data. The trade balance in the data is on average significantly higher than the model, and as a consequence, the domestic expenditures are lower. This is because the model is an endowment economy and thus the trade balance is driven purely by foreign debt service dynamics. In the data, Russia is a resource-rich country much of whose production is allocated to exports. A richer model could capture this, but the goal of this paper is to focus on the new information acquisition dynamics, to which we now turn our attention.

4.2. Information Acquisition Behavior

What is novel in this model is the state-contingent acquisition of information: More information is endogenously acquired and priced during crises. By ‘crisis’ here, we mean states of heightened spreads and default risk. It is in these states that the forecaster begins to pay more attention, for by doing so they can reduce the investors’ exposure to return risk.

We can see this in the information acquisition policy function in Figure 4, which provides the solution to the forecaster’s problem in equilibrium. Notice that the forecaster does not expend any information resources for the vast majority of output and debt levels. When output is at steady state, the forecaster only begins paying attention when debt levels are a bit above the ergodic mean of 61%. When it is less than this, he pays no attention. This debt threshold above which attention begins to be paid is increasing in output. When the country is in a deep recession, the forecaster pays attention for significantly lower debt levels, and when the country is in a large boom, he never pays any attention.

Recall that the decision whether or not to pay attention lies on a continuum of $\rho_t \in [0, 1]$. While the optimal policy is relatively binary, there are intermediate states where attention decisions are interior. For instance, in a deep recession, attention decisions in the range $[0.45, 0.55]$ are interior.

It is also worth noting that the forecaster continues to pay attention as debt levels increase, reaching a plateau a bit below unity. This is because there is little *uncertainty* of default behavior in high debt regions of the state space, but there is still substantial uncertainty from the stochastic recovery rate in this region, which is what the forecaster is learning about.

We see the consequences of this forecaster behavior in the pricing functions, which are also in Figure 4. We see that for low debt levels, there are no price differences across signal realizations. This is because the forecaster is not paying attention at these levels, and so the signal is useless and hence not priced. However, at higher debt levels, the forecaster begins to pay attention and thus the signal contains useful information. Figure 4 shows that, when in a deep recession, spreads can be more than double at the ergodic mean of debt levels as a result of bad signals received by the forecaster.

Figure 3 shows how information flows leading up to a typical default. We observe that they are literally zero for years leading up to the default event, but once output falls drastically the forecaster instantly begins to pay intense attention. Following the sudden contraction in output prior to the default, the forecaster sets the correlation coefficient near (but just below) unity and keeps it there until the default actually takes place.

It is this sort of behavior that generates additional heteroskedasticity in the country risk spreads. More information flowing to the investors during a crisis implies that orthogonal shocks (here, recovery shocks) that were priced at their unconditional mean before are now being priced with highly accurate information, which increases price volatility. In the next section we explore this phenomenon more concretely.

4.3. Heteroskedasticity (Time-Varying Spread Volatility)

A key result following the information acquisition is that our model endogenously amplifies state-contingent variation in sovereign spread volatility (or spread heteroskedasticity). Spreads exhibit increased volatility during crises when lenders price the unobserved shocks more accurately rather than considering them to be at their mean, which they do during non-crisis times.

To assess our model’s ability to generate state-contingency in the spread volatility, we propose a model-free metric of heteroskedasticity that we call the **Crisis Volatility Ratio** or CVR.²⁶ It is defined as follows: In a series of data, either simulated or empirical, let \hat{T}_x

²⁶Typically, when measuring time-varying volatility, the literature imposes quite a bit of structure. For instance, Melino and Turnbull (1990) and Fernández-Villaverde et al. (2011) measure the impact of time-varying volatility in the context of a

denote the set of all periods in which the change in the spread from the prior period is above the $(1 - x)$ percentile of its distribution for some small, positive number x . We follow Aguiar et al. (2016) in calling such events “crises.” By construction they are much more likely to happen than default events and are always observed in the data even if a default is not. With this notation, we define the CVR for a given crisis threshold x as

$$CVR_{x,w} = \frac{1}{|\hat{T}_x|} \sum_{t \in \hat{T}_x} \frac{\hat{\sigma}_{t:t+(w-1)}}{\hat{\sigma}_{t-w:t-1}}$$

where $\hat{\sigma}_{t_1:t_2}$ is the sample standard deviation calculated using the periods from t_1 to t_2 . CVR compares the volatility in a window of w periods immediately prior to a crisis to the volatility in a window of w periods after. Neither window includes the crisis itself, i.e., from $t - 1$ to t where crisis events occur at $t \in \hat{T}_x$. If the CVR is larger than one, then post-crisis periods tend to be more volatile than pre-crisis periods. Table 3 shows empirical CVRs for a panel of 23 emerging markets with a variety of frequencies; additional details can be found in Appendix B. The average across them at a quarterly frequency is 2.36 when $x = 2.5\%$ and $w = 5$. It suggests that a typical emerging market features crises that more than double the volatility on impact.

To give a sense of the metric, any AR(1) process would feature an average CVR equal to one regardless of x or w , since the volatility of the innovation is independent of any prior observation. However, a model designed to generate heteroskedasticity, such as an AR-ARCH or an AR-ARCH-M model, will feature CVRs greater than unity. To see this, we simulate both AR-ARCH and AR-ARCH-M models defined as follows:²⁷

$$s_t = \kappa_0 + \rho_s s_{t-1} + \gamma \sigma_t + \sigma_t \epsilon_t, \quad \text{and} \quad \sigma_t = \omega + \alpha_1 \epsilon_{t-1}^2$$

where s_t is the spread, ϵ_t is a sequence of iid errors following $N(0, 1)$. Notice that α_1 governs the persistence of volatility in the above model and γ determines the impact of volatility on spreads. An AR-ARCH simply sets $\gamma = 0$ where an AR-ARCH-M allows it to be non-zero.

stochastic volatility model. Imposing this or another similar structure to measure the quantitative efficacy of the model would be inappropriate in our case, since we know that the data-generating process for the simulated data is not a stochastic volatility model.

²⁷An AR-GARCH-M or a similar variation could also be used to generate heteroskedasticity with similar results. We favor an ARCH to a GARCH specification for two reasons: First, the CVR behaves quantitatively very similarly across both; second, when we do estimate this model, the EMBI data appear to favor an ARCH to a GARCH, at least for the case of Russia. When we allow for the additional GARCH parameter, the ML procedure routinely sets it to zero, i.e., its lower bound.

We then calculate CVRs from simulating these two models for 1.5 million periods under different parameterizations of (α_1, γ) .²⁸ Across different parameter pairs of (α_1, γ) , we all other parameters to their MLE values, which we provide later, and adjust κ_0 and ω until the simulated series has both a mean of 3.1% and a volatility of 2.2%, which is consistent with the spread data for Russia as well as the model. In Table 4, we report the CVR comparative statics and demonstrate that these models indeed can generate CVRs greater than unity, but in this case a large γ is required to bring the CVR into the empirically relevant range.

We first compute the CVR for the Russian data (the first column in Table 5) in the same time window. We can see that heteroskedasticity is a strong feature of the data by this metric: When $x = 2.5\%$ and $w = 5$, the CVR in the data is 2.67. Russia in this period is typical of emerging markets in general, since Table 3 tells us that this figure is within half of a standard deviation from the mean.

Our benchmark model (the second column in Table 5) comes fairly close to matching this non-targeted moment at 2.70. To get a sense of our model’s relative performance, we consider three alternative common existing models. First, we re-calibrate our benchmark model assuming infinite information costs and not matching the attention fraction; it is effectively a variation of Aguiar et al. (2016) with recovery and default cost curvature. This alternate calibration can be found in Table 1 as well. It is known that calibrated default models can replicate some of the state-contingent second-order dynamics of bond spreads (de Ferra and Mallucci [2022]) as the bond price elasticity is higher in high debt regions. Our model corroborates this finding insofar as the no-information model offers a CVR at about 2.18. This is higher than an AR(1), but it also falls quite short of both the data and the benchmark model.

Next, we estimate via maximum likelihood an AR-ARCH and an AR-ARCH-M model on the Russian spread data. We report the CVRs in Table 5 as well.²⁹ For these latter models, the parameters are estimated to capture not only the first two spread moments,

²⁸Note in order for the model to be stationary, α_1 is bounded above by unity. The same sequence of innovations is used across all parameterizations.

²⁹Parameter estimates and associated confidence bands can be found in Appendix C.

mean and variance, as our benchmark model does, but rather the entire spread distribution. Nevertheless, both the AR-ARCH and the AR-ARCH-M yield CVRs less than 1.6, which is also short of both the data and the benchmark model. While these models, designed to generate conditional heteroskedasticity, *can* generate CVRs in the empirically-relevant range, they do not at the maximum likelihood parameters. In comparison, our benchmark still generates the most heteroskedasticity and is closest to the data as measured by CVR.

4.4. Comparative Statics

To understand further how information acquisition affects the model dynamics, we consider a comparative static across information costs. These comparative statics can be found in Figure 5, the subfigures of which are plotted in log-scales along the information-cost axis.

We observe first that the attention fraction, i.e., the share of periods in which intense attention is paid to the country by the forecaster, is roughly monotonic in information costs. It rises as information costs fall, as is to be expected. This indicates that our choice of identifying information costs with the attention fraction was valid.³⁰

The reason why the attention fraction is not perfectly monotone is because default, which is the source of risk in the model, is endogenous. Thus, as the attention fraction changes, it may change the sovereign’s incentive structure to default, both unconditionally and in key, important regions of the state space. Despite these general equilibrium effects, the attention fraction is broadly monotone in information costs, as are most of the other moments we consider here.

Our key novel moment, the CVR, is similarly nearly monotonic in information costs. The effect is also quite large and fairly immediate once the attention fraction lifts away from zero. Hence the cost of information plays a key role in generating this empirical prediction, which happens to match the data well as we’ve already observed. Spread volatility is also fairly monotone, which is to be expected as more orthogonal information is priced as information

³⁰If we continue to reduce information costs, the model dynamics change very little from the minimum level in Figure 5. This is because even when information is near free, default is a rare event. The forecaster will still choose not to pay attention most of the time because default risk is effectively zero. This implies that the attention fractions does not rise much above 25% or so no matter how low we set the information cost.

costs fall.

Information costs interact with other, more standard model moments as well. We observe in Figure 5c that risk premia, which correspond to unity minus the risk-neutral share, fall substantially with information costs. This is intuitive: Cheaper information implies that investors know more, and thus demand less compensation for the risk.

Debt levels, however, are quite flat as information costs fall, despite the risk premium falling. The reason is because borrowing costs do not actually change much across information costs. Figure 5d reveals that the lower risk premium does not actually result in lower borrowing costs as measured by the average spread, but instead an increase in default risk. The reason why the heightened default risk does not translate through to higher spreads is because the risk premium is simultaneously falling.

The final thing to note pertains to the key cyclicalities of the spread and the trade share. In particular, both attenuate toward zero as information costs fall. This is because prices are driven mostly by output shocks at higher information costs, which implies strong negative correlations with output. As information becomes cheaper, though, prices begin to contain other information as well, which attenuates these cyclicalities in a fairly pronounced way. Attenuation of these moments improves its fit to the data, which would otherwise exhibit too strong a countercyclic relationship with output.

4.5. Potential State-Contingency in the Risk Premium

A further potential consequence of the model regards the composition of the risk spread and how it could change across states. To understand this, first note that we can intuitively break the spread on sovereign debt into two categories: Risk (default, dilution, and recovery risk) and a risk premium for that risk.

When the forecaster pays the cost to observe normally unobserved states, investors learn more about the realization of those shocks. In particular, the conditional volatility $\sigma_{m|x}$ shrinks. This pushes down the competitively priced risk premium. This occurs even in the case when signal $x_t = 0$ and merely supports the prior of the lenders, which is that $m_{t+1} = 0$.

This has potential implications for equilibrium prices. While default risk is high, so too is

the lenders' ability to learn and contain that risk since they are acquiring more precise signals about unobserved shocks. This implies that around a crisis their effective risk-aversion is lower and thus that the risk premium comprises a smaller share of the spread. Were an econometrician not to take this effect into account, instead employing a more standard sovereign default model in which the investors' attention set is non-state-contingent, she might wind up *underestimating* the underlying risk around crises by assuming the risk premium to be higher than it actually is.

Our model allows us to quantify this compositional shift in the risk spread. In particular, we compare the unconditional median of the risk premium as a share of the spread to its median value during a crisis. We do this for both the benchmark calibration and for the (re-calibrated) model with no information flows. These results can be found in Table 6. Our findings corroborate the intuition just laid out insofar as the risk premium tends to shrink during crises in the benchmark model while it increases during crises in the no-information version. The intuition is, again, that when information flows are endogenous greater information flows during crises mitigate the uncertainty and lower the effective risk faced by the lenders.

The size of the effect, however, is fairly small quantitatively. The reason for this is that the forecaster is effectively acting on behalf of the lenders and thus acquires information precisely when their risk profile is most threatened and to the rough degree that investors would like him to interfere given the cost. This implies that the effective risk faced by the investors does not change too much across states. Thus, while the presence of costly information has large impacts on the heteroskedasticity of country risk spreads, it does not substantively affect the decomposition of those spreads across states.

4.6. Transparency Policy

The last result we highlight regards the benefits and costs of transparency in light of our model mechanism. Costly information acquisition can be interpreted in many ways in the context of our model. One way the unit information cost κ can be understood as is the level of transparency that a sovereign has about its domestic affairs and finances. Interpreted this

way, our model can also offer some intriguing insights for sovereign transparency.

Our model suggests that transparency is a double-edged sword. When there is zero transparency, i.e., information is infinitely costly, lenders always demand a risk premium for the unobserved shocks, especially during crisis times. This makes it more expensive for the sovereign to borrow and service debt. Having more transparency will benefit the sovereign by lowering the risk premium. On the other hand, when the sovereign is fully transparent, while risk premium for the unobserved shocks disappears, it is replaced by substantial spread volatility, since now what used to be unobserved shocks are always reflected in bond prices. This not only hurts the sovereign because the country is risk-averse, but it also works to increase the default frequency, as we saw in the previous section. This implies that there are generally more deadweight loss costs incurred in equilibrium.

Therefore, transparency brings about two forces: There is the benefit of lower risk premia, but also the cost of higher price volatility and default. To illustrate this insight, we show the sovereign's welfare levels as given by certainty-equivalent-consumption levels along different information costs in Figure 6, which is evaluated at three different regions of the state space: (1) the ergodic mean of debt with steady state output, (2) zero debt with steady state output, and (3) at a 'debt crisis,' in which we set output to be two standard deviations below steady state and debt to its average level immediately preceeding a default.

We observe first that all welfare changes in information costs are miniscule relative to other model fundamentals such as output and indebtedness. Figure 6a reveals that welfare is all but flat in information costs. Welfare changes by much more by moving around in the fundamental state space. The reason for this flatness is not that information costs have no effect. As we observed earlier, they have a massive impact on risk premia, default risk, heteroskedasticity, and spread cyclicalities. Rather, the relative flatness comes from the fact that the two opposing forces brought in by more transparency more or less cancel each other out.

Further, if we zoom in on a particular state, we see that there are non-monotonicities in welfare as these two forces compete with each other. Which wins out thus depends on the

state. At the ergodic mean, there is no clear winner. Occasionally more transparency is better and occasionally less.

During a debt crisis, though, and, interestingly, at the zero debt state, more transparency is typically though not always better. For the former, this is likely because more accurate pricing of debt means slightly better prices on average, while the latter it is likely because the sovereign will experience less price volatility in its relatively long trek from zero to the ergodic mean; the prospect of higher default is not as worrisome to this country, as it will be some time before this becomes a real risk.

5. Empirical Analysis

The calibrated model yields interesting implications and may leave one wondering whether these results are specific to our benchmark calibration or whether they hold more generally. Figure 7 shows a positive co-movement between investor attention and sovereign bond spreads for a broad range of countries.

We now conduct a reduced-form empirical analysis for a abroad set of countries to validate the predictions of the quantitative model. We estimate the following equation using the daily EMBI spread and Bloomberg publication share data over the period of 2008/3/3–2016/3/14 for 28 emerging economies:

$$B_{it} = \beta_0 + \beta_1 IA_{it} + \beta_2 IA_{it} Crisis_{it} + \beta_3 z_i + \epsilon_{it} \quad (6)$$

The dependent variable B_{it} is the daily measure of sovereign bond spread moments for country i . Here we use two different measures to get a robust picture: logged daily EMBI and its (rolling window) standard deviation. We include the standard deviation as a dependent variable because our theoretical model also predicts a rise in spread volatility when investor attention increases. The standard deviation is calculated over the current date and the previous four days. For the standard deviation regressions, we also include logged daily EMBI level as a control variable to remove any alternate impact from level effects.

IA_{it} is the measure of investor attention: the share of Bloomberg news stories of country i

among those of all 61 countries on which Bloomberg reports news-heat data.³¹ In [Appendix E](#), we also use Bloomberg readership data as the investor attention measure in robustness checks.

$Crisis_{it}$ is a dummy variable that is equal to zero during normal times and one during crises. A crisis is defined the same way as before when CVR is calculated, that is, a period in which change in the EMBI from the prior period is above the 97.5 percentile of its distribution, follow [Aguiar et al. \(2016\)](#). We allow the publication variable to interact with the crisis dummy, which measures how the impact of the investor attention on bond spreads shifts during crises. z_i is a country fixed effect.

The first two columns in [Table 7](#) show the daily-data regression results. We can see that the publication's relations with the EMBI and its standard deviation are statistically significant and positive during the sovereigns' crisis periods but not otherwise. This is precisely what the structural model predicts: During crises the correlation between investor attention and the bond spread becomes stronger; further, spread volatility increases with investor attention because more information is priced and the model suggests that this effect is stronger in crises when information flows contain more useful information.

These empirical results are consistent with the findings of [Bi and Traum \(2019\)](#), who use newspaper data from 1840s and find that, during crisis times, state fiscal information helped investors differentiate states with sound fiscal policy from insolvent ones and thus affect state government bond prices for states that were ill-prepared for downturns, whereas it was not the case during non-crisis times.

As robustness checks, we then extend the baseline regression with more country-specific control variables. The estimated equation becomes:

$$B_{it} = \beta_0 + \beta_1 IA_{it} + \beta_2 IA_{it} Crisis_{it} + \beta_3 z_i + \beta_4 X_{it} + \epsilon_{it} \quad (7)$$

where the new addition in the equation, X_{it} , denotes a vector of control variables and includes government balance as a share of GDP, debt-to-GDP ratio, RGDP growth, inflation, and

³¹There is no particular trend shown in the news heat data for bloomberg's publication behavior or for any country during our sample period. Nevertheless, we have run regressions with detrended data, the results are consistent with those below when we use non-detrended data.

unemployment rate. For the standard-deviation regression in the 4th column we also control for spread level. In order to run the extended regression, quarterly data are used instead. More specifically, we use the quarterly J.P. Morgan EMBI data and calculate its standard deviation by averaging the daily EMBI's standard deviation for each quarter. For publication shares, we first sum up the daily number of Bloomberg publications to the total publications each quarter and then use the quarterly publications to calculate the shares. The *Crisis_{it}* dummy is calculated as before but using quarterly EMBI data.

The last two columns in Table 7 show the quarterly-data regression results. The publication's relations with the EMBI and its standard deviation remain statistically significant and positive during the sovereigns' crisis periods. More specifically, during crises, a one percentage point increase in a country's publication share is associated with a 38 percent increase in its EMBI and a 26 percent increase in its EMBI's standard deviation. The significant effect of additional information for investors during crisis is consistent with our earlier results.

6. Conclusion

Costly information acquisition plays an important role in the pricing of sovereign risk and we are able to study the quantitative impact of such an information friction. We constructed and calibrated a structural model of endogenous default and information acquisition using Bloomberg news-heat data as an attention metric to identify information costs. We demonstrated that the relationship between information flows and sovereign spread volatility is state-contingent and verified this prediction in the data. The inclusion of costly information acquisition in the model also allows us to study the welfare implication of transparency. Transparency is a double-edged sword, it not only can affect spread volatility but also has first-order effects on spread level and default risk.

Tables and Figures

Table 1: Calibrated Parameters by Simulated Method of Moments

Benchmark	Value	Target Description	Data	Model
Discount factor	$\beta=0.963$	Average Spread	3.1%	2.9%
Output cost (level)	$\theta_0=-0.697$	Average Debt/GDP	64%	61%
Output cost (curvature)	$\theta_1=0.775$	Spread Volatility	2.2%	2.2%
Lender CRRA	$\gamma_L = 0.97$	(Avg. RN Spread)/(Avg. Spread)	67%	69%
Unit info cost	$\kappa = 1.5e - 5$	Fraction of Quarters with $IA > \text{Midpoint}$	19%	17%
$\kappa = \infty$				
Discount factor	$\beta=0.9653$	Average Spread	3.1%	3.2%
Output cost (level)	$\theta_0=-0.345$	Average Debt/GDP	64%	59%
Output cost (curvature)	$\theta_1=0.416$	Spread Volatility	2.2%	2.3%
Lender CRRA	$\gamma_L = 0.92$	(Avg. RN Spread)/(Avg. Spread)	67%	67%

Notes: RN stands for risk neutral. The model is at a quarterly frequency; during calibration, model moments are annualized to match average annual spread and annual spread volatility.

Table 2: Moments: Empirical and Model-Derived

Moment	Source	Data	Model
Average spread	Directly Measured	3.1%	2.9%
Spread Volatility	Directly Measured	2.2%%	2.2%
Spread cyclical	Directly Measured	-0.52	-0.55
Average DE/Output	Directly Measured	90%	99.9%
(DE Volatility)/(Output Volatility)	Directly Measured	0.98	1.20
DE cyclical	Directly Measured	0.99	0.87
Average trade share	Directly Measured	10%	.1%
Trade share volatility	Directly Measured	2.5%	3.31%
Trade share cyclical	Directly Measured	0.12	-0.03
Unconditional Debt/GDP	Directly Measured	64%	61%
Debt/GDP Preceding Default		-	71%
Unconditional <i>Annual</i> Default Frequency	Tomz and Wright [2013]	[1.7%, 3.0%]	2.4%
Unconditional <i>Quarterly</i> Default Frequency		-	0.6%
<i>Quarterly</i> Default Probability Preceding Default		-	1.36%
Share of Defaults Below Trend Output (World)	Panizza [2022]	80%	99.7%
Share of Defaults Below Trend Output (Russia)	Directly Measured	100%	99.7%

Notes: ‘DE’ stands for ‘domestic expenditure.’ Consumption in the model better corresponds to domestic expenditure in the data as there is neither investment nor a separate government sector. The share of defaults below trend output for Russia comes from the fact that Russia has defaulted twice since the fall of the Soviet Union (1998 and 2022) and during both of those events output was below trend.

Table 3: Empirical Crisis Volatility Ratios (1994-2018)

Country	Q	M I	M II	W I	W II	D I	D II
Argentina	4.23	3.87	0.98	1.88	0.75	1.96	0.92
Brazil	2.09	2.09	2.48	2.09	1.36	1.79	1.51
Bulgaria	1.91	1.70	2.97	1.96	1.20	1.62	1.41
Chile	2.10	2.28	2.39	2.48	3.11	1.76	2.04
China	1.82	3.44	1.12	2.38	1.31	1.85	1.75
Colombia	3.38	1.91	2.54	1.70	1.14	1.60	1.22
Hungary	3.42	2.29	2.37	1.70	2.30	1.99	2.29
India	2.56	2.50	2.81	1.48	4.10	1.27	2.30
Indonesia	1.59	1.99	2.86	3.26	1.91	2.32	2.84
Latvia	1.14	0.38	1.33	1.17	0.98	1.34	1.38
Lithuania	1.49	0.85	2.06	2.15	0.66	1.67	0.68
Malaysia	3.07	3.44	3.11	2.85	1.69	1.81	1.99
Mexico	1.96	4.89	2.23	2.01	0.63	1.84	2.19
Peru	1.49	1.62	2.21	1.65	2.03	1.83	1.90
Philippines	1.23	3.06	3.25	2.57	3.57	1.88	2.63
Poland	2.33	1.70	2.69	1.85	2.14	1.78	3.70
Romania	–	3.06	7.53	2.08	4.16	1.66	0.32
Russia	3.51	9.50	2.01	1.54	2.31	1.38	1.07
South Africa	1.54	1.82	1.63	1.90	1.48	2.07	1.11
Thailand	2.12	1.74	1.57	8.19	1.45	1.82	1.44
Turkey	1.10	1.75	1.32	1.34	2.30	1.68	1.25
Ukraine	2.51	2.00	4.29	1.90	1.65	2.38	2.45
Venezuela	1.38	1.19	1.64	1.56	1.64	1.90	1.24
Average	2.36	2.57	2.50	2.25	1.91	1.79	1.72
Stdev.	1.04	1.82	1.35	1.38	1.01	0.27	0.77

Notes: In the first column we use quarterly data and set the crisis threshold and window to $x = 2.5\%$ and $w = 5$, respectively, as in the benchmark calibration. Other columns use different frequencies of the same dataset. Q means quarterly, M monthly, W weekly, and D daily. A numeral I indicates the same CVR parameters ($x = 2.5\%$ and $w = 5$) at alternate frequencies, whereas a numeral II indicates those same frequencies with x and w adjusted to match that of the quarterly data, e.g., for the Monthly II, $x = 2.5 \times \frac{1}{3}\%$ and $w = 5 \times 3$.

In the event that a crisis event occurs close to the beginning or end of the sample, we compute the sample standard deviation using the minimum of the designated window size and the available data. Using this approach, we are only unable to compute the CVR for Romania in the first column because there is only one crisis in the sample and it occurs at the second observation. Consequently, we cannot compute a sample standard deviation prior to the crisis.

Table 4: Crisis Volatility Ratios: Comparative Statics with Simulated Data

Parameter	AR-ARCH CVR	Parameter	AR-ARCH-M CVR
$(\alpha_1, \gamma) = (0.05, 0.0)$	1.20	$(\alpha_1, \gamma) = (0.80, 0.5)$	1.44
$(\alpha_1, \gamma) = (0.25, 0.0)$	1.22	$(\alpha_1, \gamma) = (0.80, 1.0)$	1.54
$(\alpha_1, \gamma) = (0.5, 0.0)$	1.29	$(\alpha_1, \gamma) = (0.80, 2.5)$	2.15
$(\alpha_1, \gamma) = (0.75, 0.0)$	1.43	$(\alpha_1, \gamma) = (0.80, 5.0)$	2.55
$(\alpha_1, \gamma) = (0.95, 0.0)$	1.61	$(\alpha_1, \gamma) = (0.80, 10.0)$	2.57

Notes: For all cases, we set the AR parameter to its MLE value for each specification and adjust κ_0 and ω until the simulated series has both a mean of 3.1% and a volatility of 2.2% as in the Russian spread data. For the AR-ARCH-M specification, we keep α_1 at its MLE value.

Table 5: Crisis Volatility Ratios: Data, Benchmark, and Alternate Models with MLE

	Data	Benchmark	$\kappa = \infty$	AR-ARCH	AR-ARCH-M
$CVR_{x=2.5\%,w=5}$	2.67	2.70	2.18	1.47	1.51

Notes: AR-ARCH and AR-ARCH-M parameters are maximum likelihood estimates. Their details are in [Appendix C](#). $\kappa = \infty$ is the case in which information costs are infinite but parameters are chosen via re-calibration to match the same moments rather than using the benchmark parameters.

Table 6: Risk Premium as a Share of the Risk Spread

	Unconditional Median	Median During Crises
Benchmark Model	0.3117	0.3100
No-Information Model (Recalibrated)	0.3371	0.3392

Table 7: Bloomberg Publication Share and EMBI at Crisis Times

Expl. Variables	Daily		Quarterly	
	log(EMBI)	log(Std. Dev.)	log(EMBI)	log(Std. Dev.)
Pub. Share	0.00 (0.35)	0.19 (0.21)	-0.03 (0.71)	2.66 (1.87)
Pub. Share \times Crisis	2.23 (1.11)	5.83 (0.67)	37.74 (13.63)	26.38 (7.10)
Other Controls	None	log(EMBI)	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	9682	9508	445	302
Adj. R-squared	0.008	0.165	0.192	0.292

Note: All regressions include fixed effects and robust standard errors. Other controls include government balance as a share of GDP, debt-to-GDP ratio, RGDP growth, inflation, and unemployment rate. For both spread standard deviation regressions, we also include $\log(EMBI)$ as a control variable. Data is from Bloomberg and CEIC. Standard errors in parentheses.

Figure 1:

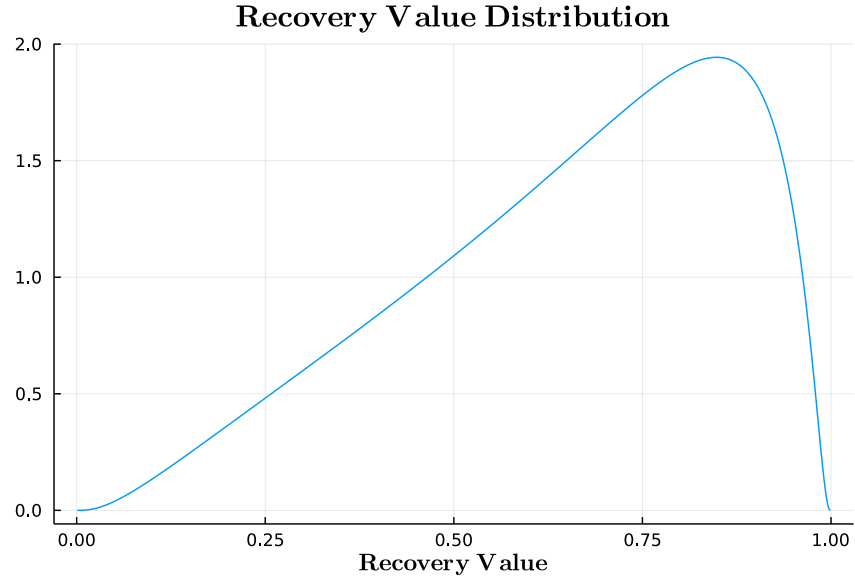


Figure 2: Model Objects: Typical Behavior for No-Info Calibration

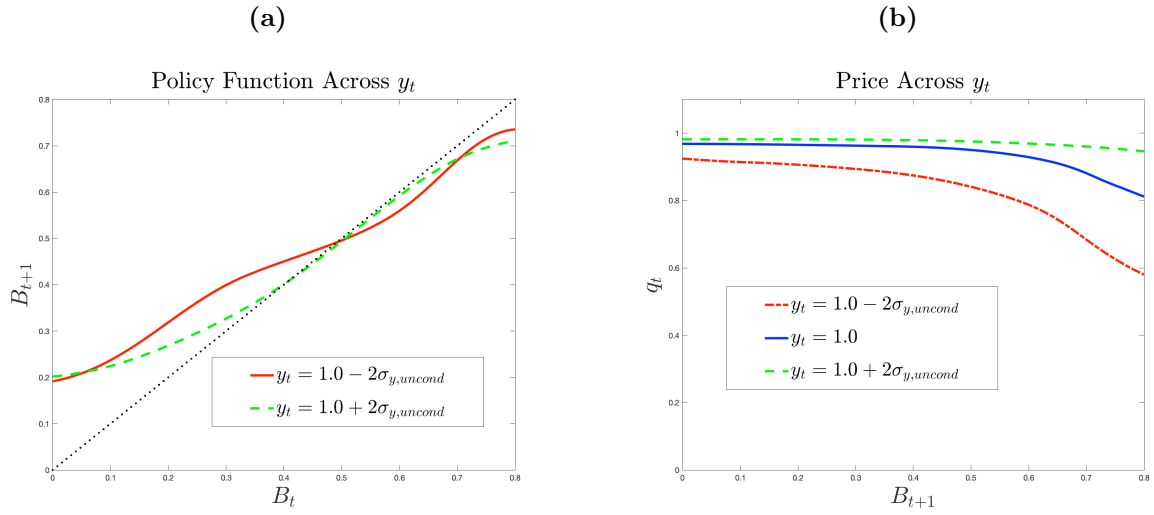
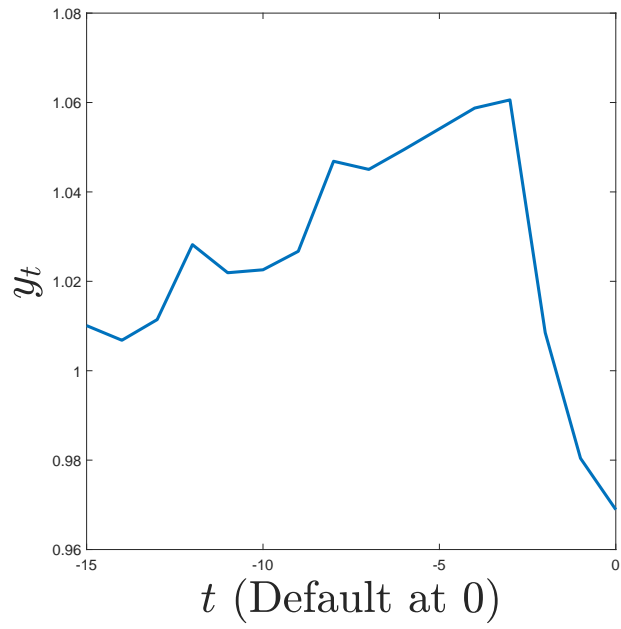
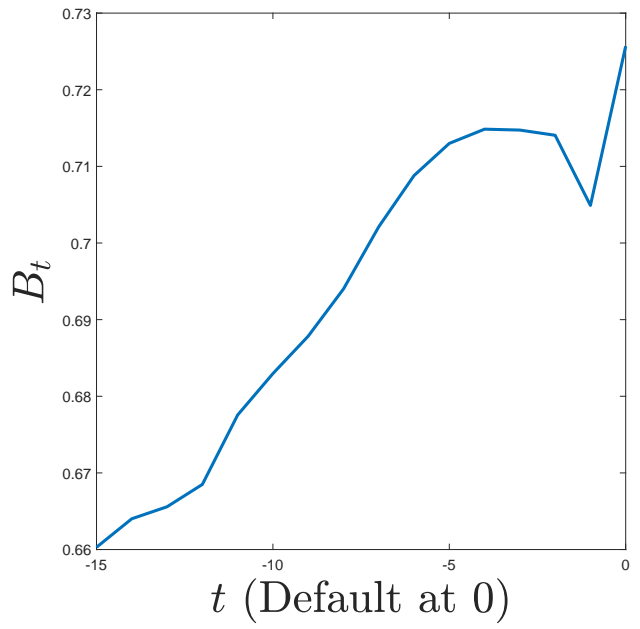


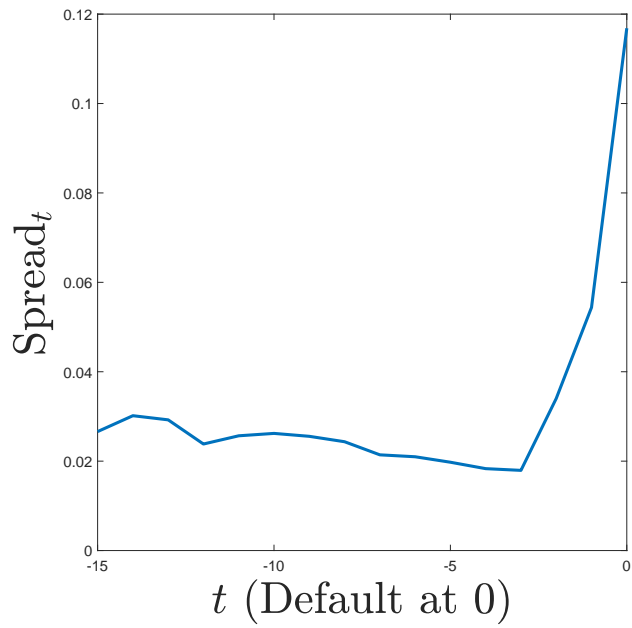
Figure 3: Typical Default for Benchmark Calibration



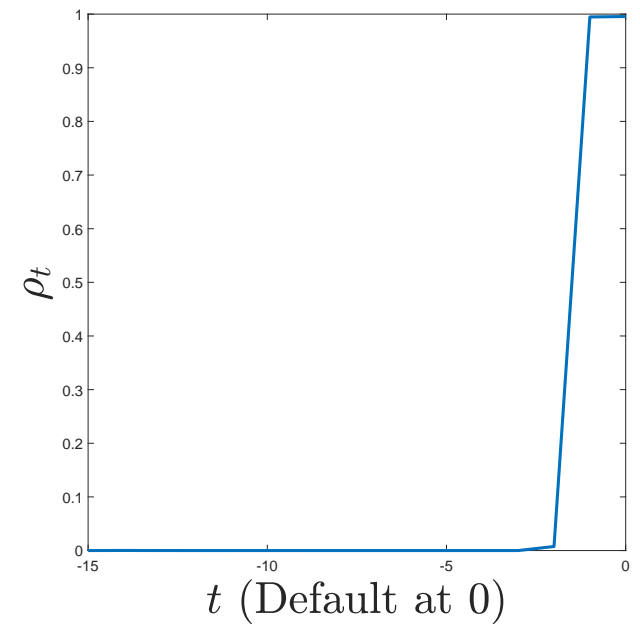
(a)



(b)

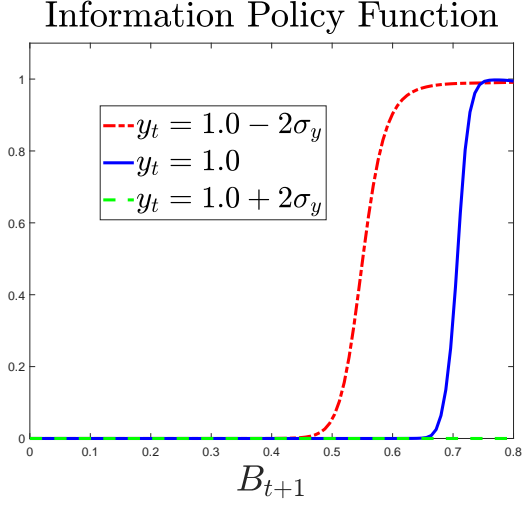


(c)

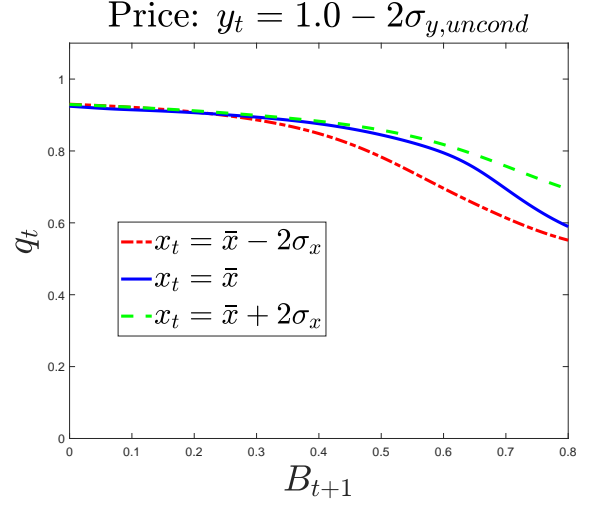


(d)

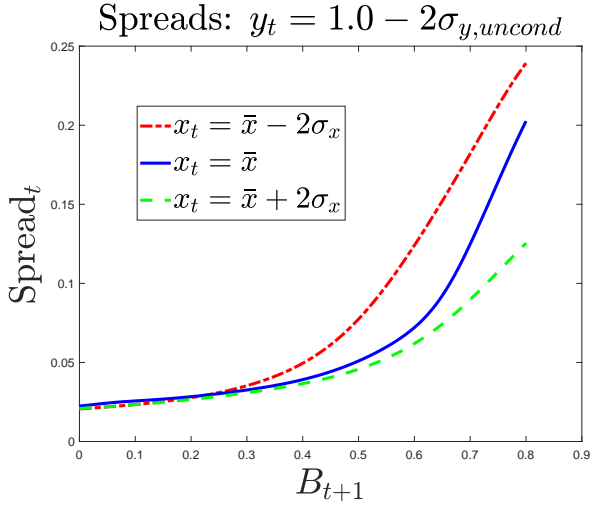
Figure 4: Information Acquisition: Model Objects



(a)

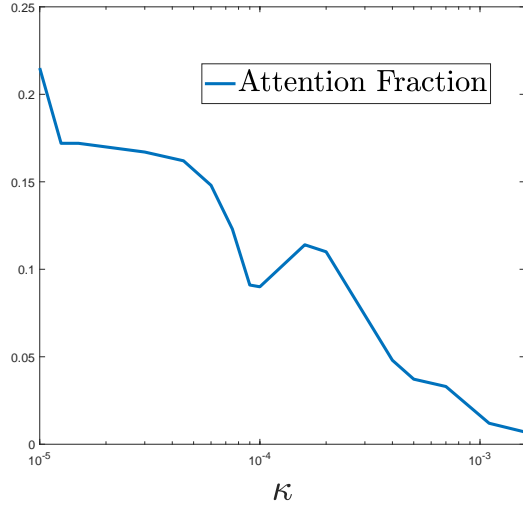


(b)

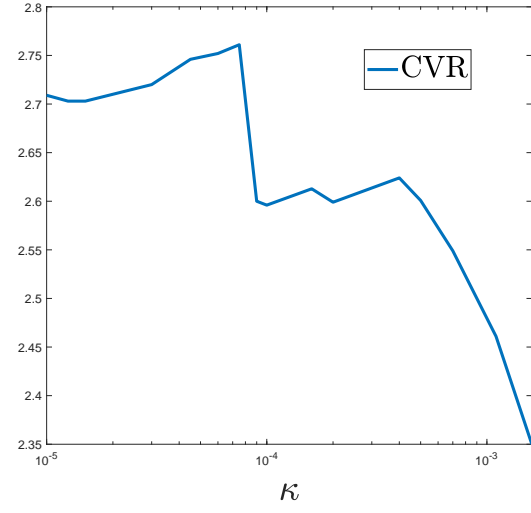


(c)

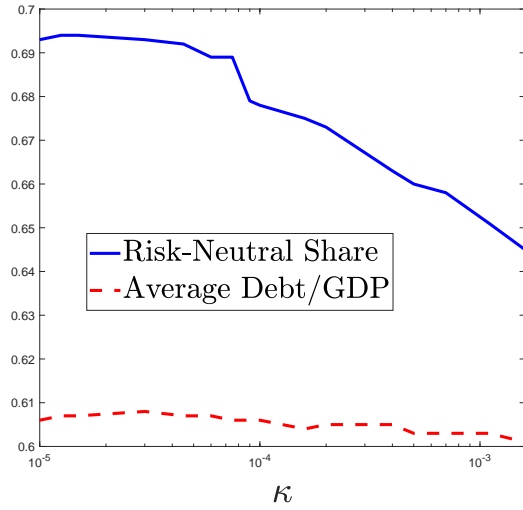
Figure 5: Comparative Static: Information Cost



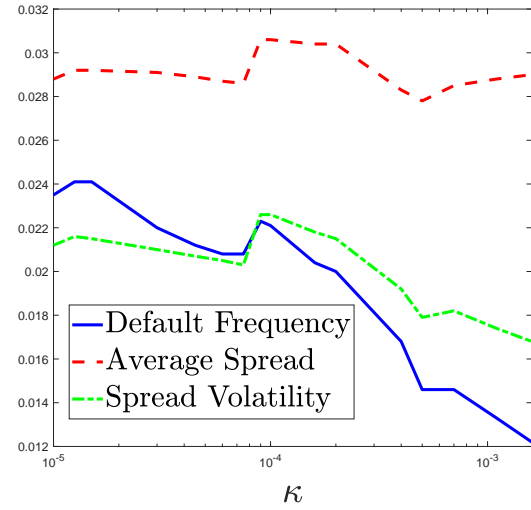
(a) Attention Fraction



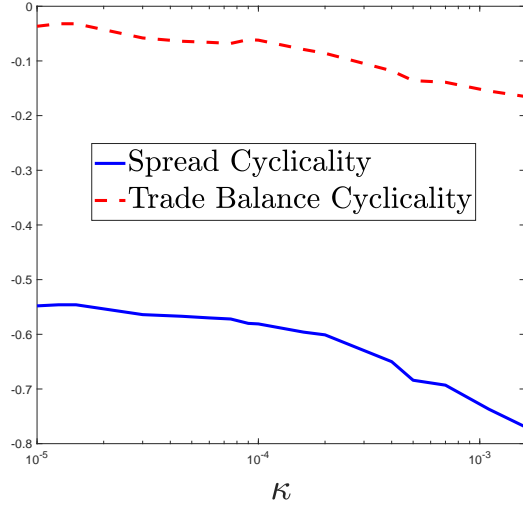
(b) CVR



(c) Debt and RN Share

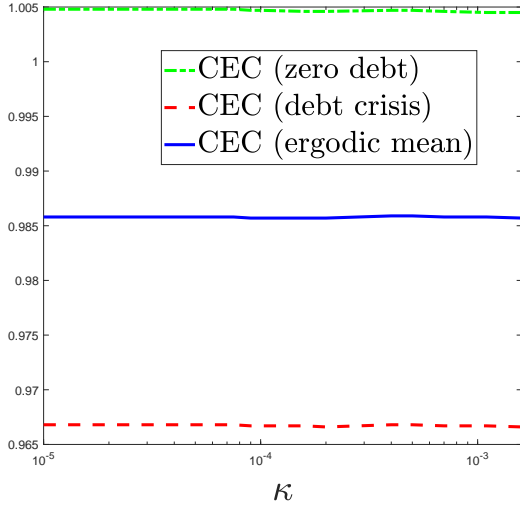


(d) Pricing Moments

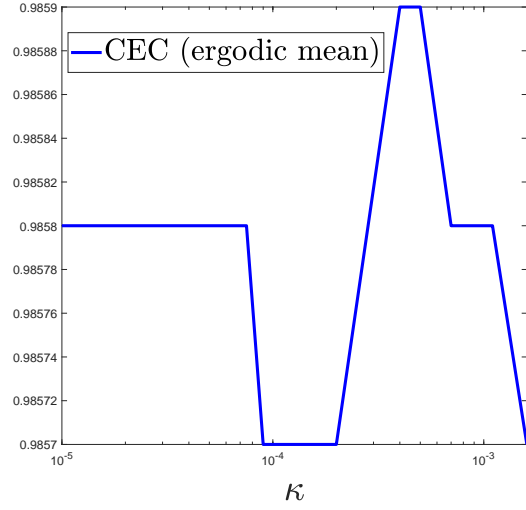


(e) Cyclicalities

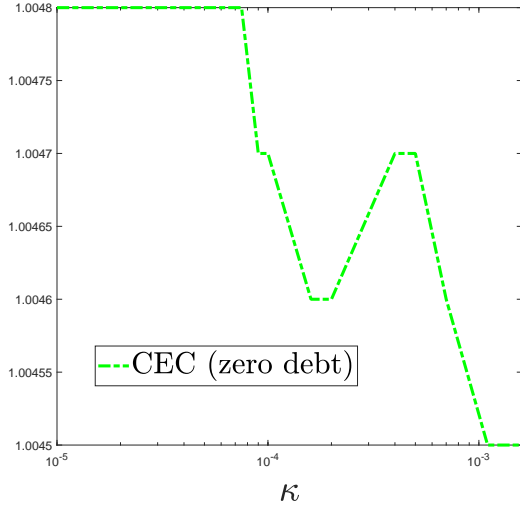
Figure 6: Certainty-Equivalent-Consumption Across Information Cost



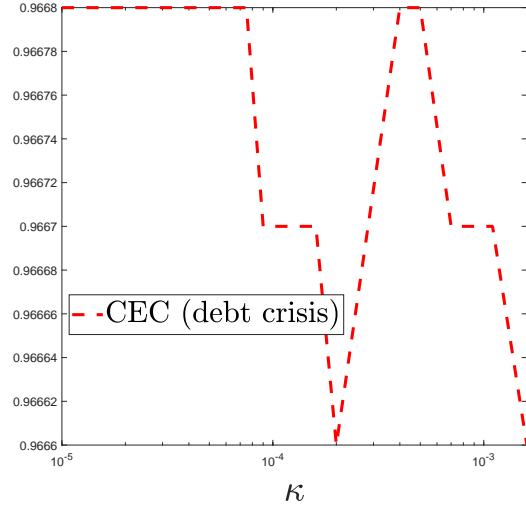
(a)



(b)

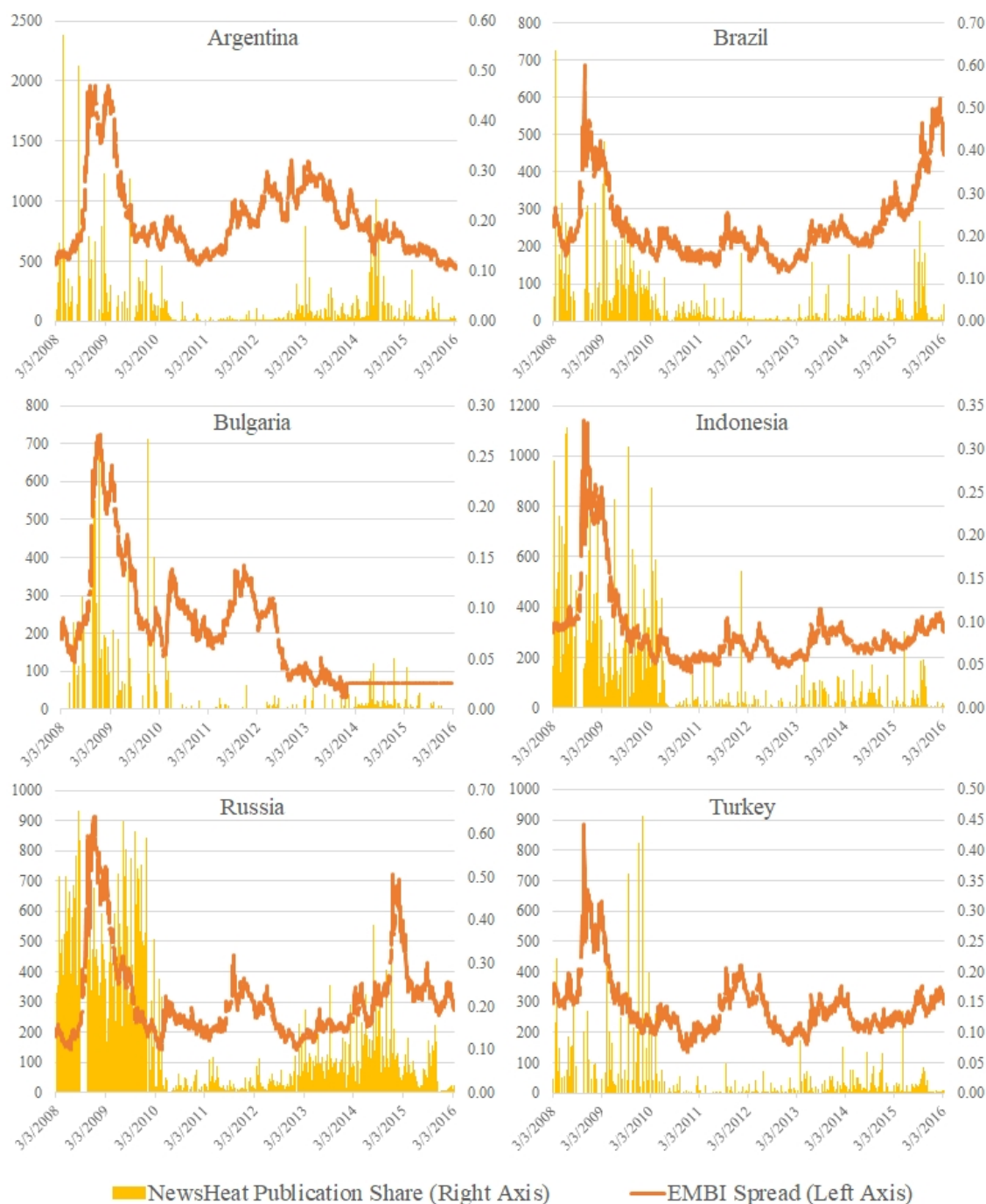


(c)



(d)

Figure 7: Bloomberg Daily Publication Share and EMBI, 2008/3/3-2016/3/14



Notes: News heat publication share is the number of Bloomberg news stories on a country divided by the total number of Bloomberg news stories on all the 61 countries that Bloomberg news heat data report, though in our empirical exercises we focus on only 28 emerging markets. There is a modest disconnect between 2010 and 2012 for many countries that seems largely to be driven by the Eurozone crisis. This crisis generated many news articles, which worked to push down the publication share of other emerging markets, but also generated contagion effects, which worked to push up their spreads.

Supplemental Appendices

Appendix A. Solution Algorithm

We solve the model using a variant of the Gaussian Process Dynamic Programming algorithm described by [Scheidigger and Bilonis \(2019\)](#), which is a machine learning algorithm. Every relevant equilibrium function is approximated by the mean of a Gaussian Process, which are derived by means of a Gaussian Process Regression (GPR). We tighten their convergence criterion to sup-norm convergence in the repayment value function of $1.0e - 6$ to ensure accuracy. We modify the algorithm along a handful of pertinent dimensions:

1. Rather than draw new training inputs (grid points) every iteration, we randomly select the training inputs from the .01% typical set (see [Cover and Thomas \[2006\]](#)) of the unconditional distribution over states, supposing all endogenous states to be distributed uniformly and independently.³²

We set bounds at three unconditional standard deviations from the mean for output and the signal. For the recovery shock, the bounds are $[0, 1]$. For the debt level, we set the bounds at $[0, .8]$.

As all draws from uniform sets are typical, for the endogenous states (here, just debt) we scramble a uniformly spaced grid with the following caveat. We split the set $[0, .8]$ at some threshold \bar{b} . We place the same number of points (uniformly spaced) in $[0, \bar{b}]$ as in $[\bar{b}, 0.8]$. We set $\bar{b} = 0.6$. This is *not* to generate more grid points in the ergodic distribution, though. The country actually spends less time in this higher sub-interval, but nevertheless we find it is important for capturing optimal behavior to have more accuracy in this region, since the sovereign may be tempted to issue large amounts of debt off-equilibrium. Accurate pricing in non-ergodic regions helps dissuade such behavior. Dividing the state space into sub-intervals is not always necessary. A scrambled uniform will suffice perfectly well for most applications.

These training inputs remain fixed across all iterations.

³²This is clearly not true in the ergodic distribution, but it suffices to draw training inputs. In a highly non-linear model such as ours, it is not clear that we would like all training inputs to fall along or near the equilibrium path. Indeed, we find that accurate functions off-equilibrium may be important for accurate on-equilibrium *decisions*.

2. We use $20 \times D$ training inputs, where D is the dimensionality of the state space.³³
3. We employ a standard Square Exponential Kernel function *without* Automatic Relevance Determination (ARD), i.e., we impose a common lengthscale. We further linearly scale all states to be in the unit hypercube before applying the GPR. We also fix the ‘measurement error’ to $\sigma^2 = 1.0e - 8$ rather than optimizing over it. We assume a mean zero prior for all Gaussian Processes.
4. For bounded functions, e.g., price and information policy functions, we apply a logit-transformation before applying the GPR. We undo this transformation when approximating the function.
5. For every function we approximate, we ‘clean’ the logit-transformed outputs by subtracting their sample mean and dividing by their sample standard deviation before applying the GPR. We undo this transformation when approximating the function.

All expectations are taken using a Gauss-Chebyshev quadrature with 15 nodes. The results do not change substantially with a finer quadrature.

Approximating all value, price, and policy functions with the means of Gaussian processes, we solve for the stationary model as a limit of the finite-horizon game following [Hatchondo and Martinez \(2009\)](#).

A brief note on convergence is appropriate. Lack of convergence is a common problem in models of long-term sovereign debt and not necessarily a failing in the solution technique.³⁴ [Chatterjee and Eyigungor \(2012\)](#) note that this stems from a non-convexity generated in the budget set by long-maturity debt. Our benchmark model and all its comparative statics are able to converge with little trouble to the requisite sup-norm tolerance of $1.0e - 6$.

Interestingly, convergence is more easily attained in the benchmark than under the no-information calibration for which convergence only rarely falls below a sup-norm tolerance of $1.0e - 4$. This is because the benchmark model generates iid fluctuations (coming from the forecaster’s signals) in the pricing function that operate similarly to (though not exactly like) the liquidity shocks added by [Chatterjee and Eyigungor \(2012\)](#) to facilitate convergence. The no-information calibration lacks this additional noise and as a consequence faces more

³³[Scheidigger and Bilonis \(2019\)](#) recommend $10 \times D$ for standard macro models, but we find that more training inputs are required to capture the high degree of non-linearity in a model of endogenous default. Nevertheless, the critical feature that the number of grid points required expands only linearly in the dimensionality of the problem survives.

³⁴We are not guaranteed that iterative methods will converge for this class of models because the Bellman equation is non-contractionary.

difficulties in convergence. For the no-information calibration, therefore, we demand a lower tolerance of $1.0e - 4$ and let the VFI run for at least 600 iterations for declaring convergence for the purpose of exercises related to this specification.

Solution code can be found at

https://github.com/zstangebye/costly_information_and_sovereign_risk

Appendix B. CVR Cross-country Statistics

Here, we provide cross-country statistics for the CVR from the EMBI dataset. Table 3 gives the CVR for the same panel of emerging economies considered in the empirical work of Aguiar et al. (2016). Different columns indicate different parameters for the CVR parameters. In the event that a crisis is near the beginning or end of a sample and this window is insufficient, we use the largest window possible. The only cases in which this is impossible is if the crisis is the second or penultimate period in the sample. This happens only once in the sample, for Romania at a quarterly frequency.

In the first column we use quarterly data and set the crisis threshold and window to $x = 2.5\%$ and $w = 5$ respectively, as in the benchmark calibration. Across columns, Q stands for quarterly, M monthly, W weekly, and D daily. A numeral I indicates the same CVR parameters ($x = 2.5\%$ and $w = 5$) at alternate frequencies, whereas a numeral II indicates those same frequencies with x and w adjusted to match that of the quarterly data e.g. for the Monthly II, $x = 2.5 \times \frac{1}{3}\%$ and $w = 5 \times 3$.

Table 3 suggests that a typical emerging market features crises that are more than twice as volatile as non-crisis times, with the quarterly average for the dataset coming in at 2.36 and most other metrics coming in near or above 2 as well. Even the lowest metric, Daily II, yields an average CVR of 1.72, implying that a CVR greater than unity is a strong feature of the data. We also provide the correlations across these different metrics in Table Appendix B.1. There is broad positive correlation across these metrics, particularly with regard to the quarterly series, which is what we use in the benchmark model. The Standardized Generalized Standard Deviation (SenGupta [1987]) is 0.86, which is smaller than the volatilities of most of the individual series, which are given in the last row of Table 3.³⁵ This indicates broad comovement across the seven series. Consequently, the exact frequency or parameter choice is not pivotal in the computation of the CVR.

³⁵For reference, if there was zero correlation across a set of series, the Standardized Generalized Variance would simply be the geometric average of the variances of the series.

Table Appendix B.1: Empirical CVR (1994-2018): Correlation Table

	Q	M I	M II	W I	W II	D I	D II
Q	1.00						
M I	0.47	1.00					
M II	0.29	0.03	1.00				
W I	0.01	-0.08	-0.05	1.00			
W II	0.31	0.13	0.57	-0.07	1.00		
D I	0.03	-0.19	0.07	0.20	-0.21	1.00	
D II	0.16	-0.09	-0.01	0.04	0.18	0.33	1.00

Appendix C. Alternative Models: Parameter Estimates

We provide here in Table [Appendix C.1](#) the maximum-likelihood parameter estimates for the Russian spread data used to compute the alternate-model-generated CVRs in Table 5. These results are robust to a wide range of initial parameters in the optimization, including all those from Table 4 designed to generate large CVRs. 95% confidence bands are estimated using the observed Fisher information matrix. Notice that in both cases, the conditional heteroskedasticity term, α_1 , is fairly large and statistically significant. The mean term in the AR-ARCH-M model, while positive, is not statistically significant.

Table Appendix C.1: ML Estimates

Parameter	AR-ARCH	AR-ARCH-M
κ_0	.0151 [−.0733,.1034]	.0239 [−.0054,.0532]
ρ_s	.8658 [.7797,.9519]	.8736 [.8229,.9244]
$\sqrt{\omega}$.0054 [.0035,.0073]	.0055 [.0041,.0068]
α_1	.7921 [.4599,1.1243]	.7935 [.4739,1.1130]
γ	N/A	−.1722 [−.5157,.1713]

Appendix D. News-heat Data Summary Statistics

Table [Appendix D.1](#) shows the summary statistics of the raw Bloomberg publication data at daily frequency during the period of 2008/3/3-2016/3/14 for 28 individual emerging economies and for all the 61 countries available, respectively. Most countries have about 4 articles on Bloomberg each day. Surprisingly, Dominican Republic has a large number of articles by Bloomberg, most of the publications actually were around June 2010–March 2011 during its election year. Among all countries, Japan had the most articles (24552) on one day, March 11, 2011, when a magnitude-9 earthquake and tsunami hit the country and were followed by a nuclear meltdown.

Table Appendix D.1: Summary Statistics of Bloomberg Daily Publication Number on Sovereigns (2008/3/3-2016/3/14)

Country	Obs.	Median	Max	Std. Dev.
Argentina	888	2	98	9
Brazil	768	4	126	14
Bulgaria	291	2	36	5
Chile	255	2	49	7
China	1695	44	649	46
Colombia	1428	2	56	4
Croatia	542	3	43	5
Dominican Republic	320	149	811	131
Ecuador	693	4	61	7
Hungary	761	3	58	7
India	1350	3	79	7
Indonesia	552	3	89	7
Kazakhstan	824	2	49	5
Lebanon	266	3	27	4
Lithuania	167	3	44	7
Mongolia	19	4	11	3
Nigeria	646	1	45	4
Pakistan	433	2	29	4
Panama	18	5	15	5
Philippines	273	3	57	8
Romania	348	3	47	6
Russia	1771	10	139	15
South Africa	303	2	49	7
Turkey	458	2	94	9
Ukraine	598	4	415	35
Uruguay	388	2	40	5
Venezuela	1182	2	123	9
Vietnam	273	1	63	6
All 61 Countries	34461	4	24552	417

Appendix E. Empirical Analysis: Robustness

Bloomberg readership data has more missing observations than the publication data, nevertheless, we use it to measure investor attention as robustness checks. It is defined as the maximum value of news heat, which reflects user activities (reading and searching news), on a specific country for the day. It is worth noting that news heat readership index does not report the absolute number of times an article being read, instead it measures readers' interest in an issuer relative to the previous 30 days, based on the number of times people call up stories with the issuer's equity ticker attached and the number of times they run the ticker looking for news. A score of 0 indicates readership is not widespread or is below the 30-day average. Scores of 1-4 indicate readership is unusually high, with 4 representing the top of the range. The daily and quarterly regression results are reported in Table [Appendix E.1](#) and are consistent with those in the previous tables. Bloomberg users become much

960 more interested in an issuer during the issuers' crisis periods.

Table Appendix E.1: Bloomberg Readership and EMBI at Crisis Times

Expl. Variables	Daily Data		Quarterly Data	
	EMBI	Std. Dev.	EMBI	Std. Dev.
Readership	-2.49	0.06	1.17	0.01
	(4.21)	(0.24)	(1.38)	(0.04)
Readership \times Crisis	36.01	6.78	7.00	0.10
	(12.56)	(2.28)	(1.06)	(0.04)
Other Controls	No	EMBI	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	1269	1269	377	311
Adj. R-squared	0.020	0.319	0.445	0.300

Note: All regressions include fixed effects and robust standard errors. Other controls include government balance as a share of GDP, debt-to-GDP ratio, RGDP growth, inflation, and unemployment rate. For both spread standard deviation regressions, we also include *EMBI* as a control variable. Data is from Bloomberg and CEIC. Standard errors in parentheses.

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