

THE PRICING OF SOVEREIGN RISK UNDER COSTLY INFORMATION*†

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We explore in a quantitative model the consequences of costly information acquisition on the pricing of sovereign risk. We develop an approach to identify information costs empirically using Google search data and find that the model generates state-dependent allocation of investor attention, which has a number of implications: First, it serves as a microfoundation for time-varying volatility in the country risk spread; second, it implies that default risk as a share of the total spread is larger near crises than a standard model would suggest, which has econometric consequences; and third, it suggests that some fiscal opacity, as opposed to full transparency, maximizes sovereign welfare.

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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 investors 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: Investors are likely to be less informed about payoff-relevant shocks in other countries ([Hatchondo \[2004\]](#), [Van Nieuwerburgh and Veldkamp \[2009\]](#), or [Bacchetta and van Wincoop \[2010\]](#)). In the information age, information about such shocks can often be acquired, but typically at a cost.

Information frictions are especially significant in the relatively illiquid market for sovereign bonds, in which most transactions occur over-the-counter and knowledge is more disperse.¹ Hence, we seek to understand how costly information acquisition affects the equilibrium pricing of sovereign default risk. In particular, we construct a model in which the sovereign's default and borrowing decisions as well as the lenders' acquisition of payoff-relevant information are jointly endogenous: Lenders can costlessly observe some public states, such as output growth and debt levels, but they cannot directly observe other potentially payoff-relevant states when they make investment decisions, such as the severity of a recession implied by a potential future default or populist sentiment in that country. Accurate information regarding these latter shocks can only be acquired at a cost.

We find that costly information acquisition generates dependence of investor attention on publicly observed states. When debt levels are low and output growth is

¹[Cole and Kehoe \(1998\)](#), [Sandleris \(2008\)](#), [Catao et al. \(2009\)](#), and [Pouzo and Presno \(2015\)](#) have all shown that information asymmetries are key to explaining various features of these markets, though none have considered the consequences of allowing information to be gathered at a cost.

high, investors are aware that there is little to no gain in terms of accurately inferring unobserved shocks since default risk is negligible for most of their realizations. Consequently, they save on information costs and acquire less information. However, for moderately high debt levels and low growth, information is more valuable since the unobserved shocks may substantially affect default risk. Thus, investors are willing to pay more to acquire information about these unobserved shocks.

Intuitively, foreign investors will start poring over more information sources during crises to carefully study the borrower and its default risk, e.g., professional forecasts, IMF staff reports, credit rating agency reports, and public finance records. This has the flavor of practical techniques employed in the financial sector, where fund managers in charge of multiple portfolios pay relatively limited attention to individual country risk unless publicly available indicators in that country trigger some preset alert. At this point, asset managers typically redirect their staff and perhaps take other means to assess more carefully that country’s risk.

To quantify the impact of this mechanism, we develop a novel strategy to empirically identify the magnitude of information costs using Google’s Search Volume Index (SVI). The literature has proposed many different measures of information acquisition (Barber and Odean [2008], Gervais et al. [2001], and Seasholes and Wu [2007]), but SVI is one of the few *direct* measures of investor “attention.” Da et al. (2011) demonstrate that it is an effective measure of attention to firm valuation and stocks, but to the authors’ knowledge the index has not yet been used to measure attention to a sovereign nation’s financial position.² In this paper, we match the fraction of quarters in which intense attention is paid to the borrower country: If information is infinitely costly, this fraction will be zero; if it is free, this fraction will be one. The

²In Appendix C, we test the robustness of the Google search index against the only other viable alternative for our framework: Extreme returns. Investor attention as measured by this alternative is strongly correlated with the Google data.

attention fraction uniformly increases as information cost decreases; thus, the latter cleanly identifies the former. We calibrate our benchmark model to Ukraine from 2004-2014, though we could perform our quantitative exercise for any country.

The model generates three new sets of results. First, it serves as a microfoundation for time-varying volatility in the country risk spread, since it generates this feature endogenously without assuming that any fundamental processes exhibit it. During normal times, investors pay little to no attention to payoff-relevant unobserved shocks. Consequently, they assume that these shocks are at their mean for the purpose of inferring and thus pricing default risk. This implies that bond yields do not respond to realizations of these unobserved shocks during normal times and so spread volatility is lower. As crises approach, however, investors pay more attention to these payoff-relevant unobserved shocks. Therefore, they are better informed about the realization of 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. This time-variation in the 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 risk-spread can have substantial first-moment effects on investment and output.

To quantify this channel we develop a model-free metric of time-varying volatility, which we call the *Crisis Volatility Ratio* (CVR). We find that in the data the CVR is 3.67. Our calibrated benchmark model, without targeting this metric, can explain almost all of it by generating a CVR of 3.04 without assuming any time-variation in the volatility of any of the underlying shocks. This is a substantial improvement over,

³Some notable recent exceptions are [Seoane \(2015\)](#) and [Johri et al. \(2015\)](#), but these papers explain time-varying volatility in the country risk spread by assuming exogenous time-varying volatility in fundamentals. [Sedlacek \(2016\)](#) provides an alternative solution, but it generates time-varying cross-sectional dispersion among firms.

for example an AR(1) process, which features an average CVR equal to 1. Further, the vast bulk of this time-variation is due to the presence of costly information acquisition, since the CVR in our model in the absence of costly information is a mere 1.22.

Second, the state-contingent nature of information acquisition has consequences for econometric inference of default frequencies from spread data. The spread on a short-term sovereign bond can be decomposed into two components: Default risk and a risk premium for that default risk. When information acquisition is costly, the relative contribution of each to the overall spread will change across publicly observed states e.g. debt levels and output growth. During non-crisis times, investors do not pay attention because it is costly; the risk premium reflects their ignorance of some potentially payoff-relevant unobserved shocks. When a crisis occurs, however, investors *respond to it* by mitigating the risk to which they are exposed via greater information acquisition. Thus, while the level of the default risk is greater, investors' effective risk-aversion is also lower.

This implies that during crises the country risk spread is mainly comprised of default risk. The calibrated model suggests that default risk constitutes about 55.2% of crisis-level spreads⁴, whereas a misspecified model without costly information acquisition would put this figure substantially lower, at about 23.2%. During non-crisis times, the average difference across these models is a mere 2.8 percentage points, so the effect is strongly state-contingent. This has substantial implications for the inference of default risk from spread data, which is a common practice in the literature ([Bi and Traum \[2012\]](#), [Bocola \[2016\]](#), [Bocola and Dovis \[2016\]](#), and [Strangebye \[2015\]](#)). In particular, it implies that a standard sovereign default model will tend to *understate* default risk during crises by assuming a risk premium that is too large.

Third, we explore the non-trivial general equilibrium effects and trade-offs as-

⁴We define a ‘crisis’ directly from spreads following [Aguiar et al. \(2016\)](#).

sociated with increasing sovereign transparency by varying information costs. We find a non-monotonicity in sovereign welfare as a function of information costs: The sovereign borrower's welfare initially increases as information costs fall, but this pattern eventually reverses and it decreases as the costs go to zero. The intuition is simple and operates through debt prices. If there is no transparency i.e. large information costs, then investors demand a greater risk premium during crises, making it more expensive to borrow and service debt precisely when the sovereign is most vulnerable. This risk premium falls as transparency increases, which is consistent with findings in the empirical literature ([Kopits and Craig \[1998\]](#), [Poterba and Rueben \[1999\]](#), [Bernoth and Wolff \[2008\]](#), and [Iara and Wolff \[2014\]](#)). This is tantamount to a reduction in borrowing costs for the sovereign, who initially exploits this by increasing borrowing, which raises default frequencies and spreads.

However, when the sovereign becomes too transparent a risk-shifting begins to occur: At high debt levels, the sovereign will be fully exposed to the volatility that results from the pricing of normally ignored unobserved shocks. This volatility causes the sovereign to delever, which reduces default frequencies and spreads. The combination of excessive volatility and subsequent deleveraging reduces the risk-averse and impatient sovereign's welfare as these low information costs become even cheaper. This latter welfare effect is a novel implication of our model. At the calibrated level of information costs, we find that some additional transparency would be beneficial, but it should not get too close to full information, lest the additional price volatility actually hurt the sovereign.

It is important to note that we are restricting attention to information frictions that are *country-specific* i.e. those that arise from between a single country and its lenders and does not apply globally. This has substantial implications for our results. For instance, one cannot account for all the time-varying volatility or the

state-contingent composition of the risk-spread by controlling for global metrics such as the CBOE VIX or the P/E ratio, as has been done in the literature (Bocola and Dovis [2016] and Aguiar et al. [2016]). With regard to the time-varying volatility, our finding corroborates the careful empirical work of Fernández-Villaverde et al. (2011), who find that the bulk of the time-varying interest rate volatility in emerging markets is country-specific rather than global.

Our focus on relations between a single borrower and its lenders over time distinguishes our analysis from the related work of Cole et al. (2016). 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. In contrast, our model highlights the capacity for costly information acquisition to generate time-varying volatility in the country risk spread and act as a potential source of bias in time-series inference.

The remainder of this paper is divided as follows: Section 2 describes the model; Section 3 discusses the data, quantitative implementation of the model, counterfactual analysis, as well as the model’s novel implications; and Section 4 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 to the recent, expanding quantitative literature, e.g., Aguiar and Gopinath (2006), Arellano (2008), Hatchondo and Martinez (2009), or Mendoza and Yue (2012).⁵ There is a sovereign borrower who issues one-period non-state-contingent debt to a unit mass of foreign lenders. This borrower lacks the

⁵For simplicity of exposition, as the above papers we restrict attention to Markov Perfect Equilibria that can be expressed recursively, though the set of equilibria is potentially much larger (Passadore and Xandri [2015]).

ability to commit to repay this debt in subsequent periods and will default if it is optimal to do so *ex post*.

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

2.1. Sovereign Borrower

2.1.1. Shocks

There are two shocks in this model, both to the sovereign. The first is a growth shock to output that the sovereign receives each period. More specifically, the endowment Y_t can be expressed in terms of a sequence of growth rates g_s as follows:

$$Y_t = Y_0 \times \prod_{s=1}^t e^{g_s}$$

where Y_0 is given. We assume g_t follows an AR(1) process:

$$g_t = (1 - \rho)\mu_g + \rho g_{t-1} + \sigma_g \epsilon_t$$

where μ_g is average growth rate, ϵ_t is a standard normal, and σ_g is the standard deviation of the growth innovation. The endowment and its growth processes are publicly observed.

The second shock in the model is an iid, multiplicative, default cost shock, \tilde{m}_t , which applies only in the first period of a default. It is the only shock that is unobserved by foreign investors when they make investment decisions (we will detail the timing below); information regarding it can only be acquired at a cost. As a default cost shock, it could represent the magnitude of capital outflows or the severity of the ensuing international sanctions among other things about which investors may not be perfectly informed. In [Appendix A](#), we also show that when \tilde{m}_t shock is log-normally distributed it can alternatively be interpreted as a default preference shock, such as

populist sentiment or political uncertainty. In this sense, \tilde{m}_t can stand in for a wide variety of payoff-relevant factors that are not immediately observed by the investors when they make investment decisions.

We collect the publicly observed exogenous states into a vector $s_t = \{Y_t, g_t\}$.

2.1.2. Timing

Following the realization of s_t the sovereign makes a default decision. Conditional on repayment, he then chooses a level of debt issuance to maximize his expected utility. Subsequently, in the middle of period t , \tilde{m}_{t+1} is realized. Lenders observe only a noisy signal of this shock and submit demand schedules to the sovereign. The sovereign then collects these schedules and from them determines a price that clears the bond market in period t . This timing can be seen in Figure I.

Notice that we assume that the sovereign cannot change its bond supply when it learns m_{t+1} . This allows us to focus on the role of information acquisition and avoid the complicated and, for our purposes, unnecessary signalling game that would ensue if it could.

2.1.3. Bond Supply and Default

As is standard in the literature, we assume a recursive, Markov-Perfect specification with limited commitment on the part of the sovereign. At the beginning of each period, it 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:

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

Given the timing assumption, we can express the value of repayment at the begin-

ning of period t as follows:

$$V_{R,t}(s_t, B_t) = \max_{B_{t+1}} E_{\tilde{m}_{t+1}} \left[\log(C_t(\tilde{m}_{t+1})) + \beta E_{\tilde{s}_{t+1}|s_t} V_{t+1}(\tilde{s}_{t+1}, B_{t+1}, \tilde{m}_{t+1}) \right] \quad (1)$$

subject to $C_t(\tilde{m}_{t+1}) = Y_t - B_t + q_t(s_t, B_{t+1}, \tilde{m}_{t+1})B_{t+1}$

The sovereign has time-separable log-preferences over consumption⁶ and is a monopolist in his own debt market. The determination of the issuance price schedule, $q_t(s_t, B_{t+1}, \tilde{m}_{t+1})$, will be discussed in the market clearing section below.

We assume that when a default happens in period t all debt is wiped out. In the first period of the default regime, the sovereign is subject to the shock m_t realized in period $t - 1$. During the entire default regime, the sovereign is excluded from capital markets for a random number of periods and faces persistent output losses. These costs are the known components of default costs and could be interpreted as a tightening of credit conditions, a disruption of trade credit, an imposition of international sanctions, or any other additional cost faced by the sovereign in default. Under these assumptions, the value of default can be expressed recursively as follows:

$$V_{D,t}(s_t, m_t) = \log(C_t) + \beta E_{\tilde{s}_{t+1}, \tilde{m}_{t+1}|s_t} [\phi V_{t+1}(\tilde{s}_{t+1}, 0, 1) + (1 - \phi)V_{D,t+1}(\tilde{s}_{t+1}, 1)] \quad (2)$$

subject to $C_t = Y_t \times [1 - \psi] \times m_t$

where ψ is the known persistent cost of a default as a percentage of output. We assume that \tilde{m}_t is log-normally distributed with a mean of 1. ϕ is the Poisson rate at which the sovereign regains access to international capital markets.

⁶None of the intuition behind our results relies on the assumption of log-utility. Any concave function will work. The benefit of using log-utility is that the unobserved shock can be interpreted either as an endowment/supply shock or as a preference/demand shock. We demonstrate this in [Appendix A](#).

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

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

2.2. Foreign Lenders

We assume a unit mass of risk-averse foreign lenders, similar 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 solves a portfolio allocation problem, deciding how much to invest in risky sovereign debt and how much to invest in a risk-free asset yielding a return, r_t .

When making information acquisition and investment decisions in period t , lenders observe s_t and B_{t+1} , but not m_{t+1} . Nevertheless, lenders do know the marginal distribution of $\tilde{m}_{t+1} \sim \ln N(0, \sigma_{\tilde{m}}^2)$ and receive noisy signals of the shock realization. We denote investor i 's signal realization as $x_{i,t+1} = m_{t+1}\mathcal{E}_{i,t+1}$ where $\mathcal{E}_{i,t+1}$ is the realized noise in the signal and comes from its distribution $\mathcal{E}_{i,t+1} \sim \ln N(0, \sigma_{\mathcal{E}_{t+1}}^2)$ with a chosen $\sigma_{\mathcal{E}_{t+1}}^2$. Lenders can improve the precision of their signals by paying for costly information, which narrows $\sigma_{\mathcal{E}_{t+1}}^2$.

Notice that this is isomorphic to choosing $\rho_{mx,t+1} = \text{corr}(m_{t+1}, x_{t+1})$. In the benchmark, we will assume that investors choose $\rho_{mx,t+1}$ because, unlike $\sigma_{\mathcal{E}_{t+1}}^2$, it is bounded.

We assume a constant information acquisition cost across investors, which implies that they all behave in the same way i.e. resort to the same $\rho_{mx,t+1}$. But they do receive heterogeneous signals and thus they offer different bond demand functions to the sovereign. This is meant to embody the realistic feature that information acquisition is in fact stochastic. Two lenders could exert the same acquisition effort but reach different primary sources that induce each to value the risky debt slightly differently. This dispersion goes to zero as $\rho_{mx,t+1} \rightarrow 1$.

There is an inherent difficulty associated with market-based information acquisition problems, which is that 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 \[1976\]](#) or [Dow and Gorton \[2006\]](#)).

We will circumvent this problem by assuming that each new generation of lenders does not know the equilibrium pricing function. Their only source of information regarding \tilde{m}_{t+1} comes from their private signal. The design of these signals and subsequent choice of demand will mimic the ‘sparse max’ operator in the recent work of [Gabaix \(2014\)](#).

While this approach, like the inclusion of noise traders ([Kyle \[1985\]](#)), places some plausible bounds on investor rationality, it is extremely tractable and consequently well-suited to our quantitative application. Further, we do not lose closeness to the literature with our novel approach: We will show in [Proposition 1](#) that our framework reduces to the textbook model of [Aguiar et al. \(2016\)](#) in the absence of information frictions.

We mimic the ‘sparse max’ operator by separating lenders’ information acquisition problem from their portfolio allocation decisions, calling them Stages I and II respectively. In Stage I, lenders choose the information set with which they will enter Stage II by minimizing a plausible quadratic loss function; in Stage II, which can be thought of as the debt auction, they solve a portfolio allocation problem given the information they acquired in Stage I.

In Stage I, all generation- t lenders are ex-ante identical. They can pay to acquire costly information regarding m_{t+1} to reduce their default risk forecast errors. As a result, each of them receives a signal $x_{i,t+1}$ from the distribution of x_{t+1} , the relevance of which depends on the chosen $\rho_{mx,t+1}$. We consider $\rho_{mx,t+1}$ as a measure of investor

attention. The information acquired is given by a time-invariant function, $I(\rho_{mx,t+1})$, which is increasing in attention $\rho_{mx,t+1}$. In the benchmark, we assume that $I(\cdot)$ is the reduction in entropy in \tilde{m}_{t+1} that comes from knowledge of x_{t+1} , but our results do not hinge on this functional form.⁷ Any increasing function would work.

We can formulate lenders' information acquisition problem as below, given s_t and B_{t+1} :

$$\begin{aligned} \min_{\rho_{mx,t+1} \in [0,1]} \quad & E_{\tilde{x}_{t+1}} E_{\tilde{m}_{t+1}, \tilde{s}_{t+1} | \tilde{x}_{t+1}, s_t} [d_t(\tilde{m}_{t+1}, \tilde{s}_{t+1}, B_{t+1}) - \bar{d}_t]^2 + \kappa I(\rho_{mx,t+1}) \\ \text{subject to} \quad & \bar{d}_t = E_{\tilde{m}_{t+1}, \tilde{s}_{t+1} | s_t} [d_t(\tilde{m}_{t+1}, \tilde{s}_{t+1}, B_{t+1})] \end{aligned}$$

where $d_t(\cdot)$ is the binary default identifier. In the benchmark model, we will assume that \tilde{m}_{t+1} is orthogonal to observed states, but the Stage I problem is flexible enough to allow for some correlation with no change in our model's mechanism: Lenders simply pay to acquire residual information that is not conveyed through observed states.

To see the benefit of information acquisition, notice that the variance of the interior expectation is decreasing in $\rho_{mx,t+1}$. Consequently, the variance in the lenders' default forecast can be reduced if the lenders are willing to undergo costly information acquisition. When s_t and B_{t+1} indicate greater risk of default, acquisition of more accurate information will tend to be optimal; when these publicly known states indicate instead that there is little to no default risk, lenders can save on information costs and accept imprecise or even orthogonal signals ($\rho_{mx,t+1} = 0$).

Once the correlation has been chosen, each lender i in generation- t receives an idiosyncratic signal $x_{i,t+1}$ and then solves the Stage II portfolio allocation problem at

⁷This notion of information was developed primarily by [Shannon \(1958\)](#) and applied to economics by [Sims \(2003, 2006\)](#). Here we have $I(\rho_{mx,t+1}) = \frac{1}{2} \log_2 \left(\frac{1}{1 - \rho_{mx,t+1}^2} \right)$.

period t . They consume only in period $t + 1$ and exhibit CRRA preferences with a risk preference parameter γ_L .

In the Stage II problem (debt auction), lenders submit to the sovereign an entire demand *schedule*: For every possible price, they specify a quantity of debt that they would purchase at that price. The sovereign then collects these schedules and announces the largest price for which aggregate issuance can be B_{t+1} .

This auction structure has a flavor of realism, since at both single and multiple-price sovereign bond auctions, lenders submit bids to the sovereign before a cut-off price is announced rather than responding to a price announcement⁸. It also has the useful feature of Proposition 1 i.e. it simplifies to a standard quantitative sovereign default model in the absence of information frictions.

Under our assumptions, each lender's bond demand schedule $b_{i,t+1}$ can be determined by solving the following problem for all price levels $q \in [0, \frac{1}{1+r}]$:

$$\max_{b_{i,t+1}} E_{\tilde{s}_{t+1}, \tilde{m}_{t+1} | s_t, x_{i,t+1}} \left[\frac{c_{i,t+1}^{1-\gamma_L}}{1 - \gamma_L} \right]$$

$$\text{subject to } c_{i,t+1} = (w_t - b_{i,t+1}q)(1 + r) + b_{i,t+1} [1 - d_t(\tilde{m}_{t+1}, \tilde{s}_{t+1}, B_{t+1})]$$

The solution to this problem is a demand schedule $b_{i,t+1}^*(q | s_t, B_{t+1}, x_{t+1})$, which is implicitly depends on $\rho_{mx,t+1}^*(s_t, B_{t+1})$. Notice that if $\rho_{mx,t+1}^* = 0$, then each lender ignores her signal since she knows it is useless. This implies that her bond demand is flat in her signal. On the other hand, if $\rho_{mx,t+1}^* > 0$, then her signal contains some useful information, and her posterior beliefs over \tilde{m}_{t+1} differ from her prior. In this case, her demand schedule responds to her signal.

Since signals can be truly correlated with the underlying unobserved shock, this

⁸An example is the Reserve Bank of India's policy, which can be found at <http://www.dnaindia.com/money/report-auction-and-bidding-process-of-government-bonds-1003719>

ignorance or use of signals is at the very heart of the model dynamics. It implies that aggregate demand will be flat in \tilde{m}_{t+1} in those states of the world in which investors do not pay attention, but it will not be flat in \tilde{m}_{t+1} in those states of the world in which they do. This implies that there are some states of the world in which \tilde{m}_{t+1} will be priced and some in which it will not be. The explicit determination of the price will be described in the next section.

2.3. Market Clearing

After the lenders offer the sovereign their heterogeneous bond demand schedules, the sovereign chooses an issuance price. Naturally, the sovereign chooses the largest price subject to the restriction that it must in fact issue B_{t+1} in the aggregate. We can use this restriction to construct the pricing schedule as follows: For any state $\{m_{t+1}, s_t\}$ and for any issuance B_{t+1} , let

$$q_t(s_t, B_{t+1}, m_{t+1}) = \sup\{q \mid \int_{x_{t+1}} b_{i,t+1}^*(q|s_t, B_{t+1}, x_{t+1}) f_{x_{t+1}|m_{t+1}, \rho_{mx,t+1}^*(s_t, B_{t+1})}(x_{t+1}) dx_{t+1} = B_{t+1}\} \quad (3)$$

where $b_{i,t+1}^*$ is the solution from lender i 's investment problem in Stage II. Notice that q_t is a function of $\{s_t, B_{t+1}, m_{t+1}\}$ but not $x_{i,t+1}$, because it is based on the aggregation of all lenders' signals. Moreover, q_t is affected by lenders' attention choice $\rho_{mx}^*(s_t, B_{t+1})$, since the latter affects not only $b_{i,t+1}^*$ as discussed above but also $f_{x_{t+1}|m_{t+1}}(x_{t+1})$. When ρ_{mx}^* is high, the signal mean depends on the realization of m_{t+1} and thus the market price moves with m_{t+1} even though it is unknown to the lenders at the time they offer their bond demand schedules.

2.4. Equilibrium Definition

Having described the model, we can now define our equilibrium:

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

$\{V_t(s_t, B_t, m_t), V_{R,t}(s_t, B_t), A_t(s_t, B_t), V_{D,t}(s_t, m_t), q_t(B_{t+1}|s_t, m_{t+1})\}_{t=0}^{\infty}$ such that

1. $V_{R,t}(s_t, B_t)$ and $V_{D,t}(s_t, m_t)$ solve Recursions 1 and 2 and imply the policy
 $B_{t+1} = A_t(s_t, B_t)$. Further, $V_t(s_t, B_t, m_t) = \max\{V_{R,t}(s_t, B_t), V_{D,t}(s_t, m_t)\}$.
2. $q_t(B_{t+1}|s_t, m_{t+1})$ is defined by Equation 3 when
 $d_t(m_t, s_t, B_t) = \mathbf{1}\{V_t(s_t, B_t) < V_{D,t}(s_t, m_t)\}$.

In [Appendix B](#), we demonstrate how this model can be stationarized for solution purposes.

We now show that our equilibrium is sensible in that it can be interpreted as a superset of a class of more standard sovereign default models.

Proposition 1. When $\sigma_m = 0$, the model becomes that of [Aguiar et al. \(2016\)](#) with permanent shocks and short-term debt.

Proof When $\sigma_m = 0$, then m_t can take only one value (\bar{m}) in Recursion 2, since the distribution over m_t is degenerate. Similarly, the expectation over m_{t+1} in Recursion 1 becomes degenerate and effectively disappears. Consequently, we can drop m_t as a state variable.

Lenders in such an environment would clearly set $\rho_{mx,t+1} = 0$ for any $\kappa > 0$. The price is then determined by the solution to the Stage II problem and the market clearing expression in Equation 3. Since all lenders ignore their signals, demand does not depend on x_{t+1} and we arrive at

$$q_t(s_t, B_{t+1}, m_{t+1}) = \sup\{q | b_{t+1}^*(q | s_t, B_{t+1}) = B_{t+1}\} = q_t(s_t, B_{t+1})$$

which is simply what the pricing function is in [Aguiar et al. \(2016\)](#) when endowment shocks are permanent and the debt is short-term.

More interestingly, when $\sigma_m > 0$ and information frictions matter for the equilibrium dynamics, the model endogenously generates acquisition of information that is contingent on observable states. During non-crisis times, information is not particularly valuable to a foreign investor. Thus, investors price sovereign debt assuming unobserved shocks to be at their average. During crisis times, however, information is highly valuable. Consequently, it is both acquired and priced, which increases the volatility of the sovereign spreads. This generates a number of interesting results including time-varying spread volatility, state-contingent risk premia that are relevant for econometric inference, and novel welfare results on transparency for the sovereign borrower.

3. Quantitative Analysis

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 Ukraine from 2004-2014. We choose Ukraine since its macroeconomic properties during this time are rather similar to Argentina during the 1990's, which is the canonical calibration choice for models in this vein ([Aguiar and Gopinath \[2006\]](#) or [Arellano \[2008\]](#)), and thus the model will have little difficulty matching the key moments. In contrast, many Latin American economies during the 2000's exhibit substantially lower growth and spread volatility than in the decades prior. Further, Ukraine was at the heart of several news cycles over the course of this period, including political upheavals during the Russo-Georgian War in August 2008 and the annexation of Crimea by the Russian Federation in early 2014, which fits especially well with our perceived examples about the unobserved shocks. Last, we choose the period of 2004-2014 because it is the only period for which Google search volume data, which is key in our approach, is available. We solve the model using value function iteration

on a discrete grid.

3.1. Data and Calibration

We take data from three primary sources: First is the JP Morgan Emerging Market Bond Index (EMBI) database taken from Datastream; second is the World Bank database; and third is Google Trends' Search Volume Index (SVI).

3.1.1. Information Cost Identification

First and most importantly, to find a proper cost value per unit information, i.e., κ , we match the variability of information acquisition in the model and in the data. Following [Da et al. \(2011\)](#), we measure information acquisition in the data by employing Google search trends for terms for which investors are likely to search. In particular, we consider Google's *Search Volume Index* (SVI), which is a scalar measure normalized to be always between 0 and 100 for the intensity of Google searches for a given term over a given time period. Zero is for minimum intensity and 100 is for maximum intensity.⁹

The process of our information cost identification is as follows. First, we obtain monthly SVI data for 2004-2016 and average them into quarterly data. Then, we transform the raw SVI series into the *Abnormal Search Volume Index* series (ASVI), as suggested by ([Da et al. \[2011\]](#)). The ASVI is meant to capture a notion of paying “extra” attention to a certain event or item in a period t . In any period t , it is computed as follows:

$$ASVI_t = \log(SVI_t) - \log(\text{Median}(\{SVI_{t-9}, SVI_{t-8}, \dots, SVI_{t-1}\}))$$

In the benchmark, we compute the ASVI for the search term “Ukraine IMF,” since

⁹In [Appendix C](#), we show that our metric is highly correlated with another common metric of attention.

investors are more likely to be interested in relevant IMF staff reports and programs than average search users. We consider other search terms for robustness in [Appendix C](#). The full ASVI series can be found in Figure [II](#). We can see that ASVI lines up well with Ukrainian political upheavals. It also slightly leads and shares a positive correlation (43%) with JPMorgan’s EMBI index for Ukraine.

After computing the ASVI, we define an information threshold $\zeta = 0.5 \times \max\{ASVI_t\}$. Our calibration target then becomes the fraction of quarters when investors acquired information about Ukraine with intensities above this threshold. It captures the frequency of large, positive, and relatively discrete jumps in attention. This is the sort of behavior that our model predicts and so it is a natural target.

For our data, the ASVI threshold $\zeta = 0.55$ and the targeted ratio is 7.1%. It captures the biggest peak in early 2014, which was largely tied to Ukraine’s conflict with Russia and the annexation of the Crimean peninsula.

3.1.2. Calibration

To obtain the output process, we estimate via MLE an AR(1) process ($\rho_g = 0.5058, \mu_g = 0.0126, \sigma_g = 0.0846$) on dollar-valued GDP growth for Ukraine from 2004-2014 at a quarterly frequency.

We assume that the risk-free rate is fixed at 1% quarterly; that the lenders exhibit constant relative risk-aversion preferences with CRRA=2, which is standard; and that $\theta = 0.083$, which is an estimate used by [Mendoza and Yue \(2012\)](#) for an average duration of 6 years before returning to international bond market. For simplicity, we also assume that lender wealth is constant over time, i.e., $w_t = w$.

We calibrate the remaining five parameters, $\{\beta, \psi, w, \sigma_m, \kappa\}$, using the simulated method of moments (SMM) to target the simulated results from our model at five moments from the corresponding data: Annual default frequency, average debt-service-to-GDP ratio, annual spread volatility, average annual spread, and fraction of time

in which information acquisition (IA) is above 50% of its max value.¹⁰

These parameters are given in Table I. Each parameter is primarily identified by its corresponding target moment, though there are significant cross-partial effects. The resulting parameterization is fairly standard¹¹ and the match is quite close. The primary exception is the spread volatility, which is a bit too low. [Aguiar et al. \(2016\)](#) show that it is difficult for this class of models to match spread volatility; [Chatterjee and Eyigunor \(2017\)](#) use this fact to motivate their exploration of political turnover in this class of models. Our unobserved volatility shock does help to bring the volatility up, but not quite to empirical levels.

In the following sections, we explore the model's quantitative implications.

3.2. Model Behavior

Before we exposit the properties that are unique to this model, we show that along many dimensions it preserves key features of a standard quantitative sovereign default model. For instance, Figure III gives the bond demand functions in equilibrium. It exhibits a simple, downward sloping feature that looks remarkably similar to [Aguiar and Gopinath \(2006\)](#) or [Arellano \(2008\)](#) despite the added complexity of signal extraction and ex post lender heterogeneity. We can see that better growth shocks lead to higher price schedules.

The equilibrium policy functions are given in Figure IV. We can see that better growth shocks lead to higher debt issuance. This is a standard feature of the quantitative models discussed in [Aguiar et al. \(2016\)](#).

Figure V provides an event study surrounding a default. Again, the model behaves as a standard model would. We can see that spreads gradually increase prior to a

¹⁰Our model and its results are at quarterly frequency. The model results are adjusted to annual statistics to match the listed annual targets.

¹¹While β may at first glance appear to be very low, it is right in the neighborhood of its estimates from similar models e.g. [Aguiar and Gopinath \(2006\)](#) or [Aguiar et al. \(2016\)](#).

default and exhibit a sharp spike the period before. This is because growth follows the boom-bust cycle documented in [Aguiar et al. \(2016\)](#): Leading up to a default is a series of benevolent growth shocks that induce excessive borrowing, which slowly raises spreads. A default occurs when the sovereign accumulates a large amount of debt in this fashion and then experiences a severe and unanticipated drop in growth.

What's novel in this model is the state-contingent acquisition of information: Investors optimally choose to acquire more information during times of crises i.e. near default. Recall from the calibration that the ergodic mean of the debt-to-GDP ratio is about 12.4%. We can see in the policy functions in Figure [VI](#) that for debt levels below this, investor attention depends on the underlying growth shock i.e. the observed shock. If growth is high, investors do not pay attention unless debt levels become very large. However, when growth is low, investors pay attention for lower debt levels. Notice further that for very high debt levels investors cease to pay attention as well: This is because default is near certain in these regions, regardless of the realization of the unobserved shocks. Consequently, there is no point paying a cost to learn about those shocks.

The bond demand schedule across m_{t+1} can be seen Figure [VII](#). For low debt levels, investors do not pay attention to these unobserved shocks and thus do not react. Hence, there is no difference across the two price schedules for debt-to-GDP levels lower than about 10% or so. As debt levels rise, though, they begin to pay attention and the schedules begin to diverge. This divergence lines up exactly with the non-zero attention regions from Figure [VI](#). Notice further that there is a non-monotonicity in the good schedule i.e. the schedule with a lower default value as a result of $m_{t+1} = -1.5\sigma_m$. This is because the extra information they obtain reveals that default is substantially less likely and thus they are willing to offer a higher price than they would for a minutely smaller debt level for which they did not acquire this

information.

What do these policy functions imply for the behavior of endogenous objects? Figure [VIII](#) provides a graph of lenders' optimal signal correlation leading up to a default event. We can see that attention increases during such crises: Signal precision is relatively low 9 quarters prior to the event i.e. during non-crisis times. As observed states indicate that default risk is rising, however, investors become more aggressive in their acquisition of information, increasing it from an average of about $\rho_{mx} = 0.04$ to $\rho_{mx} = 0.15$ on the cusp of a default event.

The acquisition of more information near defaults or crises has a number of interesting implications that we will explore over the next few subsections.

3.3. Comparative Statics and General Equilibrium Effects

We now discuss how the model responds to changes in information costs and, in doing so, highlight the non-trivial general equilibrium effects of information cost reduction on sovereign behavior.

The state-contingent acquisition of information has monotonic effects on some model moments and non-monotone effects on others. This is shown in Figure [IX](#).

The first panel shows that higher moments and attention variables are monotonically reduced by information costs. As information costs decrease, the fraction of time investors spend paying attention to the sovereign and the spread volatility and skewness increases significantly. The intuition for the former is trivial and was in fact used for the calibration; the intuition for the latter is that cheaper information means that unobserved m -shocks get priced more often instead of being assumed at their average. This naturally increases spread volatility. Skewness rises almost monotonically in response to cost reduction because the impact of uncovering knowledge about the m -shock has an asymmetric impact on the spread: Good news reduces the spread mildly, at best to the risk-free rate, while bad news can cause massive spikes. As

information costs fall, the frequency of these massive spikes increases, which pushes up the skewness.

The second panel of Figure IX shows that mean debt levels, spreads, and default frequencies are non-monotonically affected by reductions in information costs. This is because of an interesting and non-trivial general equilibrium impact on sovereign behavior. As we reduce information costs from very high levels, investors are more informed and thus require a lower risk premium, which lowers borrowing costs, encourages borrowing, and raises default frequencies and spreads.¹²

However, as information becomes too cheap, risk is transferred from the lenders to the sovereign and spread volatility dramatically increases. The risk-averse sovereign does not like such high levels of price volatility, and endogenously chooses to delever to reduce his exposure to them. This deleveraging reduces default risk and average spreads.

3.4. Implications and Results

3.4.1. Time-Varying Volatility

The first result is that our model endogenously generates time-variation in sovereign spread volatility. In the model, spreads exhibit increased volatility during crises, since lenders price the unobserved shocks more accurately, rather than assuming them to be at their mean, which they do during non-crisis times to save on information costs. Further, the time-varying volatility is strongly countercyclical and positively correlated with spread levels. This implies that one could interpret our framework as a micro-foundation for such models as [Melino and Turnbull \(1990\)](#) or [Fernández-Villaverde et al. \(2011\)](#).

To assess our model's ability to generate time-variation in the spread volatility, we

¹²This reduction in the risk premium will be documented explicitly in Section 3.4.2.

propose a model-free metric of the time-variation, which we call the **Crisis Volatility Ratio** or CVR.¹³ It is defined as follows: In a series of data, either simulated or empirical, let \hat{T} denote the set of all periods in which the change in the spread from the prior period is above the 97.5 percentile of its distribution. We follow [Aguiar et al. \(2016\)](#) in calling such events “spread crises,” and by construction they are about $7.2 \times$ more likely to happen than default events and can be observed in the data even if a default cannot. With this notation, we define the CVR as

$$CVR = \frac{1}{|\hat{T}|} \sum_{t \in \hat{T}} \frac{\hat{\sigma}_{t:t+w}}{\hat{\sigma}_{t-w-1:t-1}}$$

where $\hat{\sigma}_{x:y}$ is the sample standard deviation calculated using the periods from x to y . This ratio compares the spread volatility in a window of w periods immediately prior to a spread crisis and that for w periods after, excluding the spread crisis event itself (from $t-1$ to t). In the benchmark, we set $w = 5$. If it is larger than one, then crisis periods tend to be more volatile than non-crisis periods. To give a sense of the metric, any AR(1) process would feature an average CVR equal to one since the volatility of the innovation is independent of the any prior observation.

We compute the CVR for the data and two different model scenarios: Our benchmark model and a model with infinitely costly information. The results are given in Table [II](#). We can see that time-varying volatility is a strong feature of the data by this metric: The CVR is more than 3.5 times what an AR(1) would suggest. This is no surprise, as strong time-variation in the volatility was documented by [Fernández-Villaverde et al. \(2011\)](#).

What is surprising is the capacity of our model to explain this. Our benchmark

¹³Typically, when measuring time-varying volatility, the literature imposes quite a bit of structure. For instance, [Melino and Turnbull \(1990\)](#) and [Fernández-Villaverde et al. \(2011\)](#) can measure the impact of time-varying volatility in the context of a 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.

model can explain roughly 83% of this non-targeted metric i.e. 3.04 out of 3.67. Further, much of this explanatory power is due almost solely to costly information acquisition. To see this, we compare our model to two different counterfactuals and report the CVRs in Table II: First, we re-solve the model for the same parameters but with infinite information costs, such that unobserved shocks are never priced. Our model generates a 128.6% increase in the CVR (from 1.33 to 3.04) relative to the this counterfactual. Second, we re-solve the model with the same parameters but no information asymmetries i.e. $\sigma_m = 0$. Our model generates a 149.2% increase in the CVR (from 1.22 to 3.04) relative to the this counterfactual.

While our benchmark model is calibrated to match the data while these counterfactuals are not, Table II also gives the relevant model moments for these counterfactual models, which are certainly in the empirically relevant neighborhood for a typical emerging market.

It is worth noting that there is some time-variation in volatility in the model even without information frictions. This is simply because even those publicly known shocks' fluctuations are not always relevant for default risk and consequently are not always priced. This implies lower price volatility in normal times than crises. This is true in any model of endogenous sovereign default and, to our knowledge, is a previously undocumented finding. Nevertheless, our model's ability to more than double this underlying the time-variation in spread volatility and thus bring it to empirically relevant levels is substantial and noteworthy.

Further evidence of the power of costly information acquisition to generate time-variation in the spread volatility can be found in Figure X, which gives the percent increase in the CVR from the infinite-cost counterfactual for a wide range of different information costs. It makes clear that the CVR is monotonically decreasing in the information cost. Further, this relationship is quite steep, with the full-information

model generating a near 300% increase over the no-information model.

3.4.2. Default-Risk Inference

The second result we highlight is that the composition of spreads is not the same during crisis times and non-crisis times. To understand this, first note that we can intuitively break the spread on sovereign debt into two categories: default risk and a risk premium for that default risk.

$$Spread_t = Default\ Risk_t + Risk\ Premium_t$$

When lenders pay the cost to observe normally unobserved states, they learn more about the realization of those shocks. Hence, they can better assess that risk and the risk premium decreases.

What does this imply for default risk inference? While default risk is high during a crisis, so too is the lenders' willingness to learn and contain that risk since they are acquiring more precise signals about unobserved shocks. This implies that their effective risk-aversion is lower and thus that the risk premium comprises a relatively smaller share of the spread during a crisis than during normal times. Consequently, if an econometrician were not to take this into account, instead employing a more standard sovereign default model with constant investor attention to infer default risk from spread data, she would *underestimate* default risk during crises: She would assume the risk premium to be higher than it actually was.

Our model allows us to quantify the bias resulting from this mis-specification. To do so, we construct an artificial, non-equilibrium no-information price schedule, which prices the exact same default risk as the benchmark but under the assumption that $\kappa = \infty$. We then compare simulated spreads from the benchmark model to this alternative spread series.

We then consider the following event study: We isolate crises not driven by m -

shocks i.e. the top 2.5%ile of the spread change distribution of the no-information counterfactual spread series, which does not price m -shocks. We further condition on such crises in which $m_{t+1} = 1$, and thus the benchmark spread is not unusually high or low as a result of learning, since in these cases informed investors did not learn that this shock was anything but average. The only difference between the two spread series during such events should be the risk premium: In the benchmark model it will be lower than in the no-information counterfactual, since more information is acquired during a crisis in the benchmark model.

We isolate all such events in a simulation with length 1.5 million periods, and we compute the median share of default risk as a fraction of the total spread. The stochastic impulse-response function can be found in Figure [XI](#). During a crisis, the benchmark model puts this figure at 55.2%, while the no-information counterfactual puts this same figure at 23.2%, a difference of 32 percentage points. The average difference between the series in non-crisis times, on the other hand, is a mere 2.8 percentage points, an order of magnitude smaller.

Thus, default risk *as a share of the total spread* increases by substantially more during crises than a misspecified model without costly information acquisition would suggest. This implies that if an econometrician used such a misspecified model to infer the implied default risk from, say, a crisis-level 15% spread, she would likely impute a default risk around 3.5% when the true default risk is likely closer to 8.2%.

This default-risk composition is particularly interesting since it follows from the fact that risk-premia depend on *country-specific* states. Thus, it cannot be controlled for using global metrics, such as the CBOE VIX or the P/E ratio, as is often done ([Aguiar et al. \[2016\]](#) or [Bocola and Dovis \[2016\]](#)). Rather, our theory suggests that in order to accurately assess default risk, some metric of investor attention, such as SVI or ASVI, must be controlled for.

3.4.3. Transparency

The last result we highlight in this paper has to do with 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. Up to this point, we have focused on the interpretation that it is difficult for lenders to acquire information about a sovereign. However, the unit information cost κ in our framework could also be understood as scaling the level of transparency that a sovereign has about its own domestic affairs and finances. Interpreted this way, our model can also offer some interesting insights for transparency policies.

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 precisely when its marginal utility is the highest. Having more transparency will benefit the sovereign by lowering the unobserved risk premium. However, when the sovereign is fully transparent, although the unobserved risk premium disappears, it is replaced by substantial spread volatility, since now what used to be unobserved shocks are constantly priced. This will hurt the risk-averse sovereign as well. Therefore, transparency brings about a risk-shifting: There is the benefit of lower risk premia, but also the cost of higher price volatility.

To illustrate the above insight, we show the sovereign's welfare levels along different information costs in Figure XII, which is evaluated at zero debt and at the steady state growth. We can see that as the information cost decreases from the highest end, the sovereign's welfare first increases; but once the cost gets too low, its welfare eventually reverses course and decreases sharply. This is precisely because of the risk-shifting from the lenders to the sovereign that occurs as information costs fall.

The model suggests that there is some benefit to information cost reduction in the benchmark calibration, which is denoted by a star in the figure, but this reduction ought not to go too far or it could be self-defeating by amplifying price volatility.

4. Conclusion

In this paper, we explored the consequences of costly information acquisition on the pricing of sovereign risk. We constructed and calibrated a structural model of endogenous default and information acquisition, making novel use of Google search data.

We demonstrated that costly information acquisition generates country-specific time-varying volatility in sovereign bond spread; implies a compositional shift in that spread during crises; and highlights both the benefits and costs for emerging markets' welfare with regard to increasing transparency. We also laid the groundwork for information cost identification strategy through relevant attention metrics.

Possible extensions to our framework could include rollover crises in the vein of [Cole and Kehoe \(1996\)](#), long-maturity debt ([Hatchondo and Martinez \[2009\]](#) or [Chatterjee and Eyigungor \[2012\]](#)), or persistent unobserved shock processes. The intuition of our results would not change with any of these extensions, though the quantitative results may be affected.

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Appendix A. Proof of Isomorphism Between Preference and Cost Shocks

Notice that under log-preferences, we can express the value of default as

$$V_{D,t}(s_t, m_t) = \log(Y_t \times [1 - \psi]) + \log(m_t) + \beta E_{\tilde{s}_{t+1}, \tilde{m}_{t+1}|s_t} [\phi V_t(\tilde{s}_{t+1}, 0, 1) + (1 - \phi)V_{D,t}(\tilde{s}_{t+1}, 1)]$$

which implies that we can define $\hat{V}_{D,t}(s_t) = V_{D,t}(s_t, m_t) - \log(m_t)$, where $\hat{V}_{D,t}(s_t)$ is the value of default when the only cost of defaulting is $\phi(g_t)$.

With this notation, the default decision can be written as

$$d_t(m_t, s_t, B_t) = \mathbf{1}\{V_{R,t}(s_t, B_t) < \hat{V}_{D,t}(s_t) + \log(m_t)\}$$

In this isomorphic environment, m_t becomes a preference shock to the benefit of defaulting.

Appendix B. Solving the Model

We consider the more general case of CRRA preferences for simplicity of exposition. We stationarize this model by dividing the sovereign resource constraint in every period by Y_t , and the value functions by $Y_t^{1-\gamma}$. This delivers a convenient recursive structure which is independent of both time and the level of output. We denote $b' = B_{t+1}/Y_t$ and $c = C_t/Y_t$.

$$v_R(g, b) = \max_{b' \geq 0} E_{\tilde{m}'} \left[\frac{c(\tilde{m}')^{1-\gamma}}{1-\gamma} + \beta E_{\tilde{g}'|g} e^{\tilde{g}'(1-\gamma)} v(\tilde{g}, b', \tilde{m}') \right]$$

s.t. $c(\tilde{m}) = 1 - b e^{-g} + q(g, b', \tilde{m}') b'$

The value of default is scaled similarly, yielding

$$v_D(g, m) = \frac{([1 - \psi] \times m)^{1-\gamma}}{1 - \gamma} + \beta E_{\tilde{g}', \tilde{m}'|g} \left[\phi e^{\tilde{g}'(1-\gamma)} v(\tilde{g}', 0, 1) + (1 - \phi) e^{\tilde{g}'(1-\gamma)} v_D(\tilde{g}', 1) \right]$$

This stationarization implies that we can express the default policy function using only stationarized model objects, since Y_t does not influences the default decision once g_t is known.

$$d(m, g, b) = \mathbf{1}\{e^{-g(1-\gamma)} v_R(g, b) < e^{-g(1-\gamma)} v_D(g, m)\}$$

The benchmark model with sovereign's log-preferences will simply be the limiting case as $\gamma \rightarrow 1$. This will imply that the stationarized model will feature log flow utility and that the impact of \tilde{g} on the effective discount factor vanishes.

With this simplification, we can stationarize the lenders' problem as well:

$$\min_{\rho_{mx} \in [0, 1]} E_{\tilde{x}'} E_{\tilde{m}', \tilde{g}' | \tilde{x}', g} \left[d(\tilde{m}, \tilde{g}, b') - \bar{d} \right]^2 + \kappa \mathcal{I}(\rho_{mx})$$

The second stage of the lenders' problem can also be stationarized as well under the assumption that $w_t = wY_t$.

$$\begin{aligned} & \max_{b'_i} E_{\tilde{m}', \tilde{g}' | x'_i, g} \left[\frac{c_i'^{1-\gamma_L}}{1 - \gamma_L} \right] \\ \text{s.t. } & c'_i = (w - b'_i q)(1 + r) + b'_i [1 - d(\tilde{m}', \tilde{g}', b')] \end{aligned}$$

We solve the model using a discretized grid over the state space: We approximate the growth process using a Tauchenized Markov process with 25 grid points; we assume a uniform grid over debt levels from $[0, .75]$ of 201 points; we discretize m_t , x_t , and $\rho_{mx, t+1}$ across 11 points each; and we discretize the lenders' price grid across 131 points, 11 of which are uniformly distributed below $q_{break} = 0.8$ while the rest are

uniformly distributed above q_{break} for improved accuracy in the most relevant regions of the state space. Relevant model moments remain essentially unchanged when we increase the size of this grid along any dimension.

Appendix C. Robustness: Alternative Measure of Attention and Alternative Search Terms

In this section we explore the robustness of our proxy for information acquisition, Google SVI.

First, we explore the correlation of our chosen attention metric, SVI, with another common metric of investor attention in the literature, extreme daily returns ([Barber and Odean \[2008\]](#)). In particular, we use daily return data on the stripped sovereign spread from JP Morgan’s EMBI database and compute the largest monthly return in absolute value. We then compare this series to the monthly SVI series in Figure [C.1](#). While they do not line up perfectly, there is much co-movement ($\rho = 0.3541$) and thus our metric lines up reasonably well with this other proxy.

Most of this co-movement is driven by extreme negative returns, which is consistent with our theory since investors pay attention more during crises. The correlation with SVI and the minimum daily return in a month is -0.5208 , which provides even further evidence of the relevance of our metric.

Another alternative considered in the literature are daily trade volumes. However, such data is difficult to acquire and may not exist for sovereign bonds. This is the case for our benchmark choice of Ukraine, for which almost all trades are executed over-the-counter instead of in an exchange.

Since it is not entirely clear what the appropriate search term should be, we con-

sider a handful of alternate search terms to ensure that we are capturing as closely as possible investor attention and not merely general inquiry searches. In addition to the benchmark term, ‘Ukraine IMF,’ we also consider the terms ‘Ukraine bloomberg’ and ‘Ukraine Reuters.’ The series are juxtaposed in Figure C.2. We can see from the figure that the benchmark term has an extra ‘spike’ during the Russo-Georgian war that the alternative terms do not. This is not a problem for us, however, since this attention spike was not large enough to place it over the mid-point, and thus our identification strategy did not count this as a period in which attention was paid. Rather, for all three terms, the only relevant spike in the sample occurred around the Russian annexation of Crimea in 2014. Further, our target calibration statistic does not vary greatly for these terms, with the fraction of high attention for ‘Ukraine bloomberg’ being 4.3% and for ‘Ukraine reuters’ being 4.4%. While these come in lower than our benchmark target of 7.1%, Figure IX (our comparative static exercise) reveals that the quantitative impact this cost difference would have on our simulated moments and quantitative results is small.

We also consider our benchmark search in other languages. Figure C.3 provides a color-coded world map showing the language of maximum search volume for each country for the three most common languages: English, Russian, and Chinese. We can see that English is far and away the most dominant language for these searches, even dominating search volume over Russian in Russia. The only exception is in China, where Chinese is dominant.

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Tables

Table I: Calibration by Simulated Method of Moments

Parameter	Value	Target Description	Data	Model
Discount factor	$\beta=0.812$	Annual Default Frequency	1.5%	1.3%
Output cost (known)	$\psi=0.0225$	Average Debt-Service-to-GDP Ratio	12.6%	12.4%
Lender wealth	$w=2.50$	Average Spread	6.4%	5.7%
Unobs shock std dev	$\sigma_m=0.0152$	Spread Volatility	5.5%	3.4%
Unit info cost	$\kappa=0.0034$	Fraction of Quarters with $IA > \zeta$	7.1%	7.2%

Table II: Crisis Volatility Ratios (First Row) and Counterfactual Moments

Data (Ukraine)	Benchmark Model	$\kappa = \infty$ Counterfactual	$\sigma_m = 0$ Counterfactual
3.67	3.04	1.33	1.22
Def. Freq.	1.3%	1.0%	0.8%
E[Debt Service/GDP]	12.4%	12.2%	14.2%
E[Spread]	5.7%	4.7%	3.9%
Std(Spread)	3.4%	1.7%	2.0%
Fraction with $IA > \zeta$	7.2%	0.0	0.0

Figures

Figure I: Timing of Events in a Period

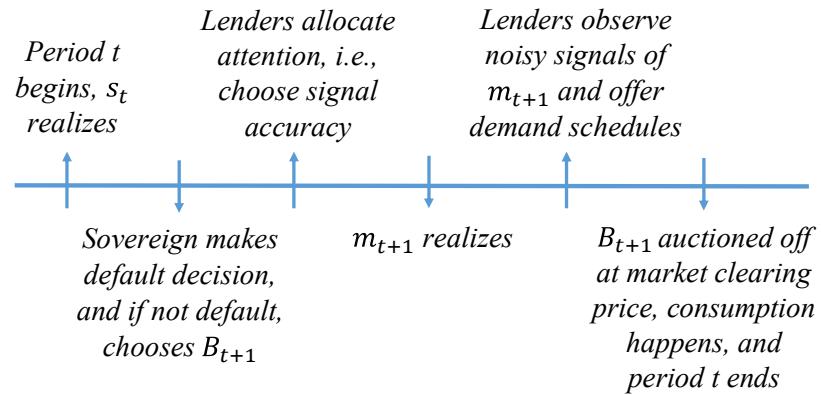


Figure II: Quarterly ASVI for the Search Term “Ukraine IMF”

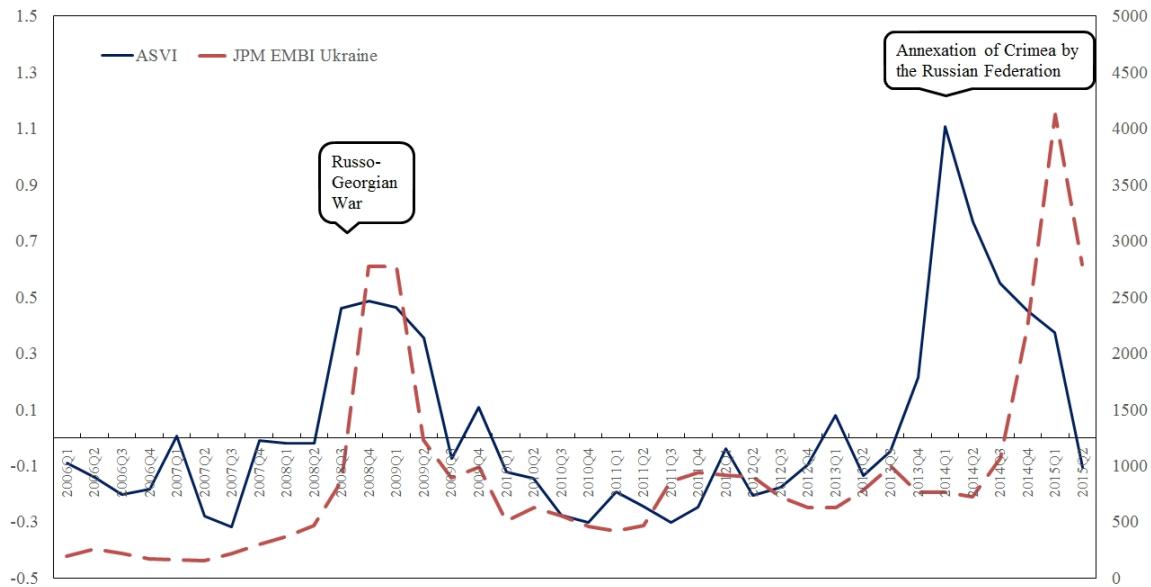


Figure III: Equilibrium Bond Demand Functions

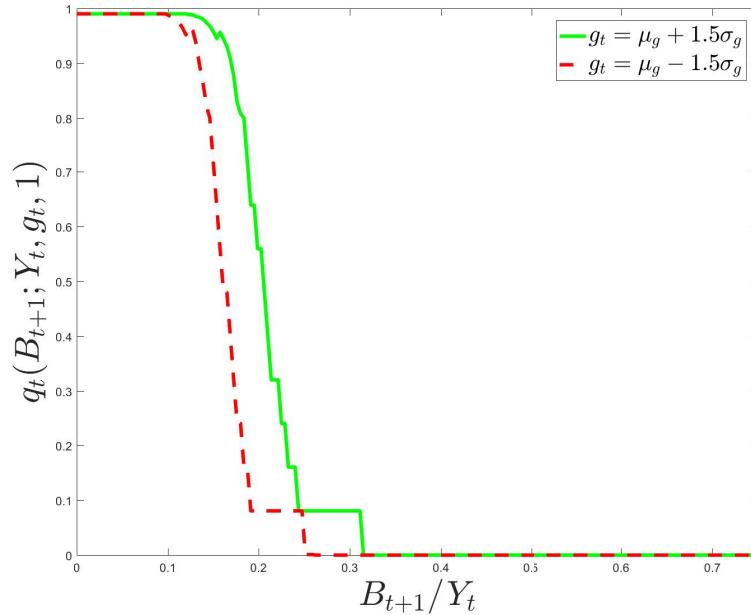


Figure IV: Equilibrium Policy Functions

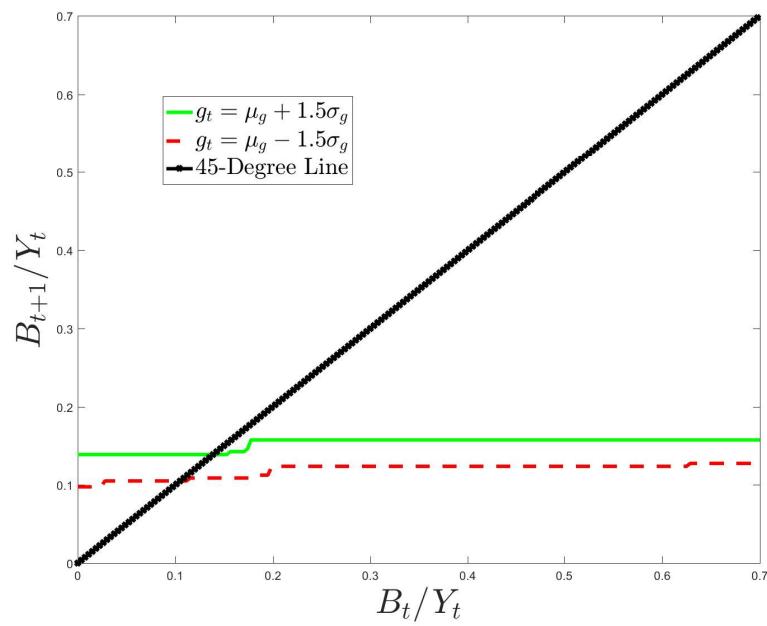


Figure V: Benchmark Behavior Around Default

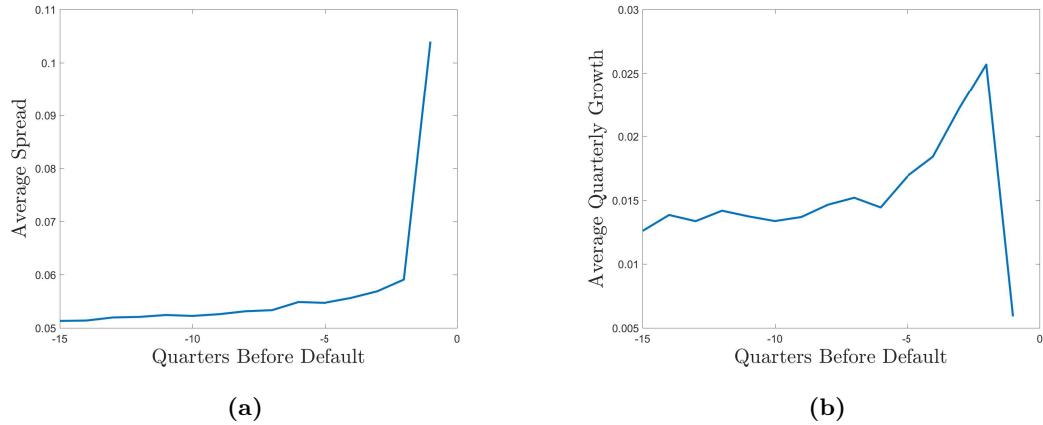


Figure VI: Information Acquisition Policy Function

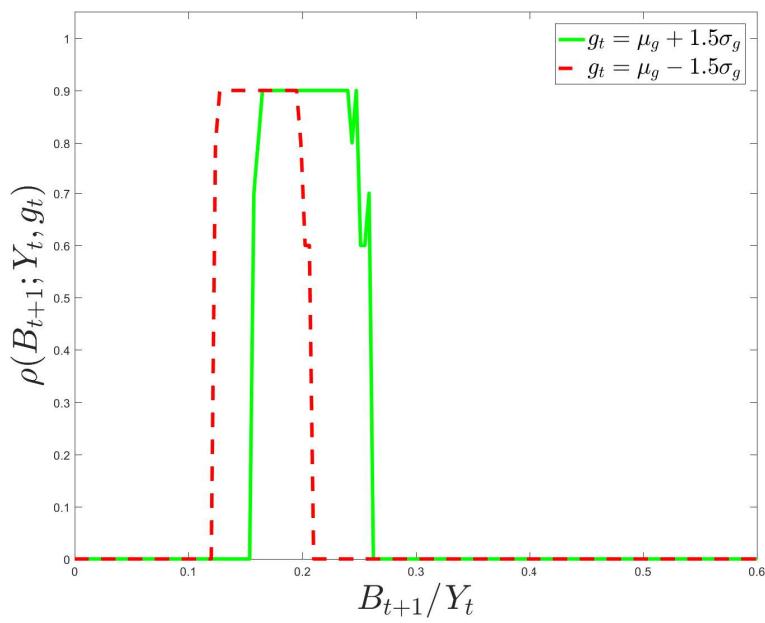


Figure VII: Equilibrium Bond Demand Functions

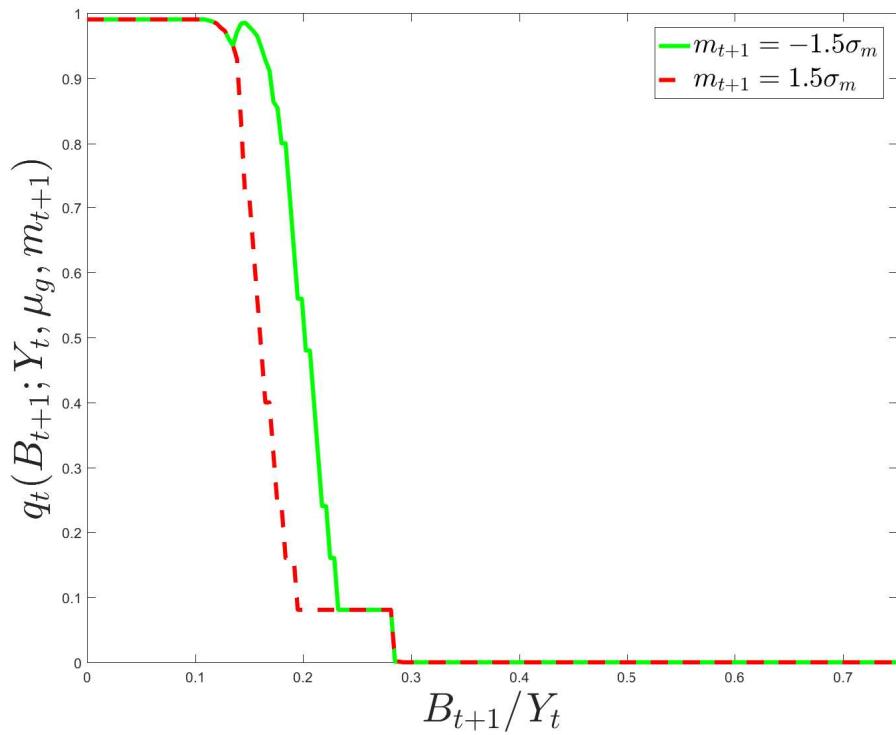


Figure VIII: Information Acquisition Before Default

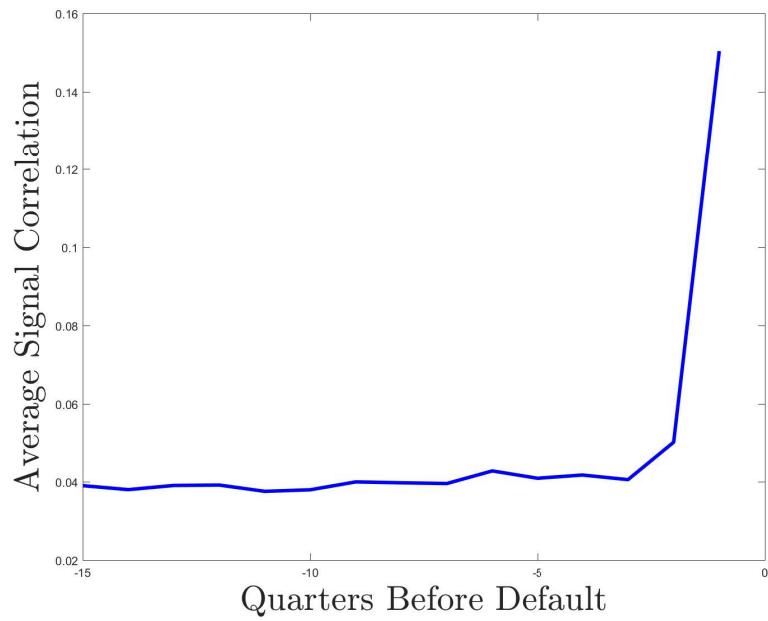
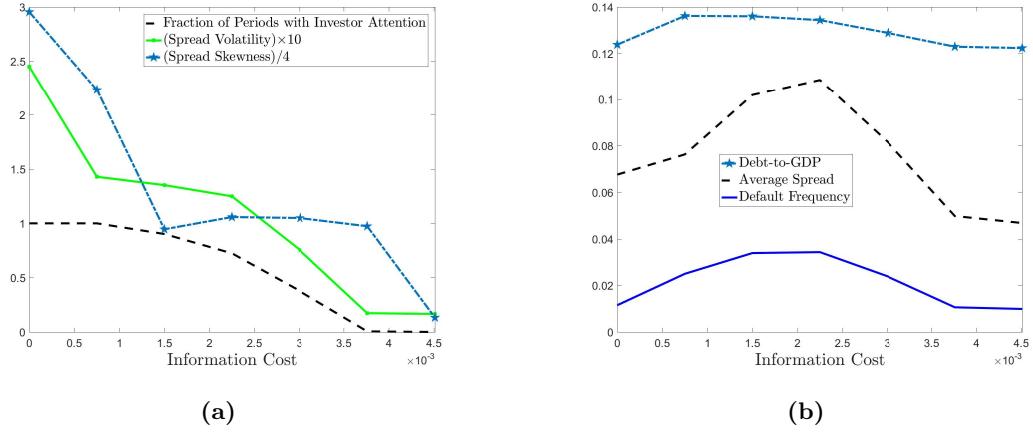


Figure IX: Model Moments Across κ



(a)

(b)

Figure X: Crisis Volatility Ratios Across κ

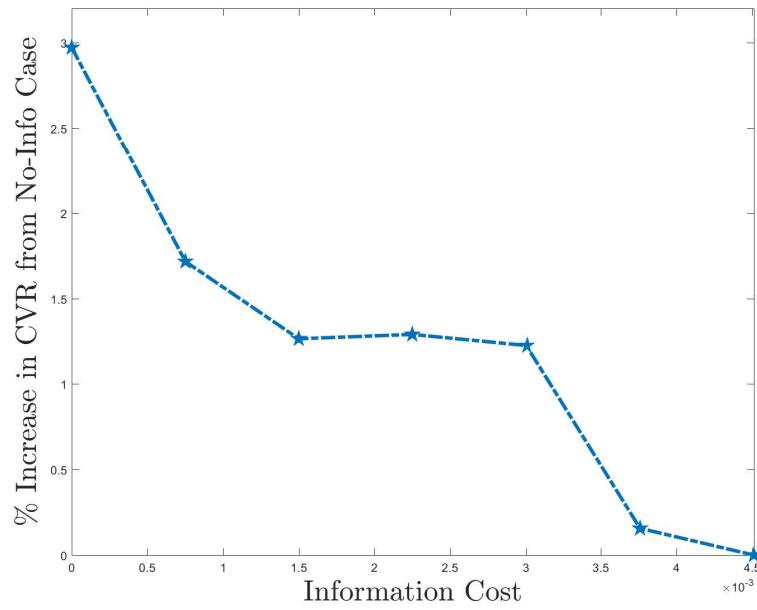


Figure XI: Spread Decomposition During Crises

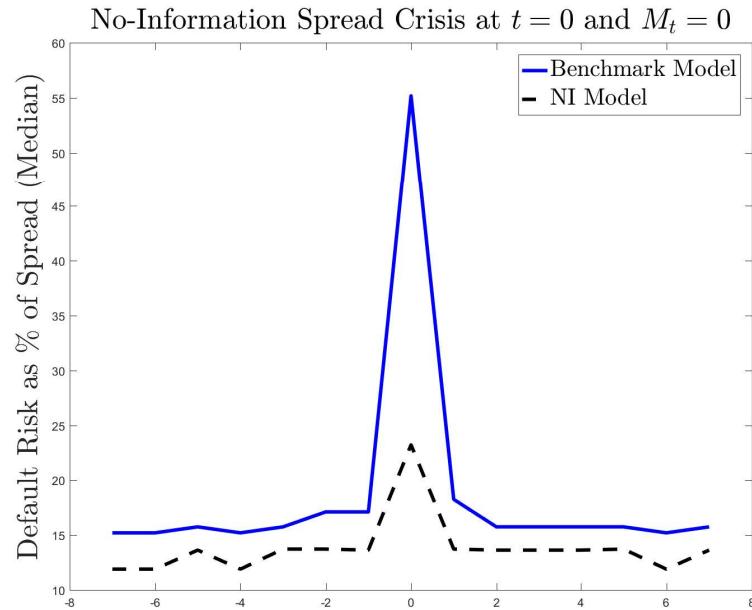


Figure XII: Sovereign Welfare Across Information Costs

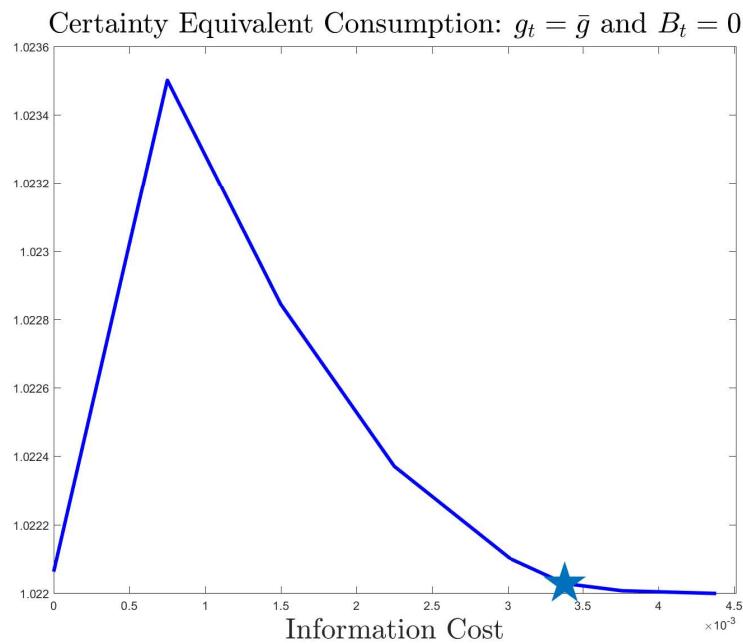


Figure C.1: Comparison of SVI and Extreme Returns

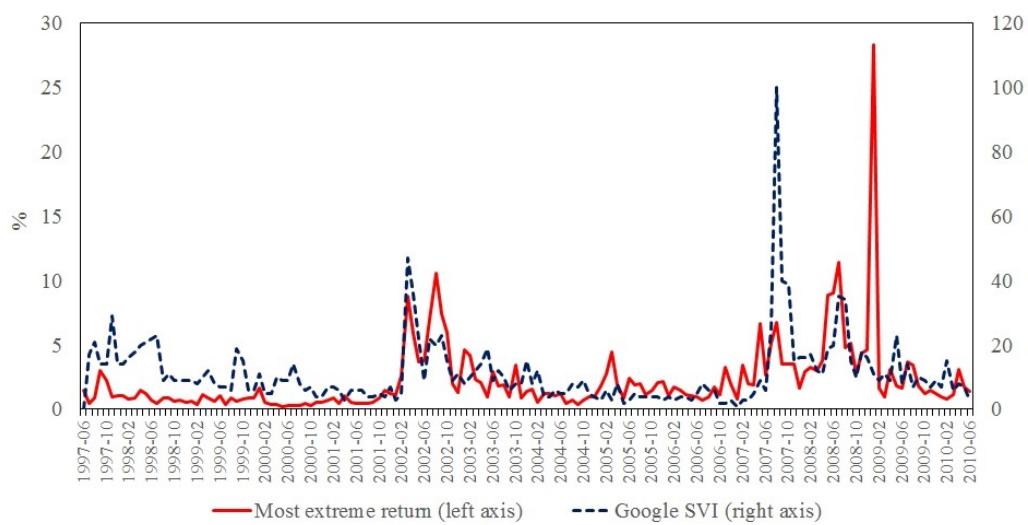


Figure C.2: Comparison of Benchmark Search Term to Alternate Search Terms

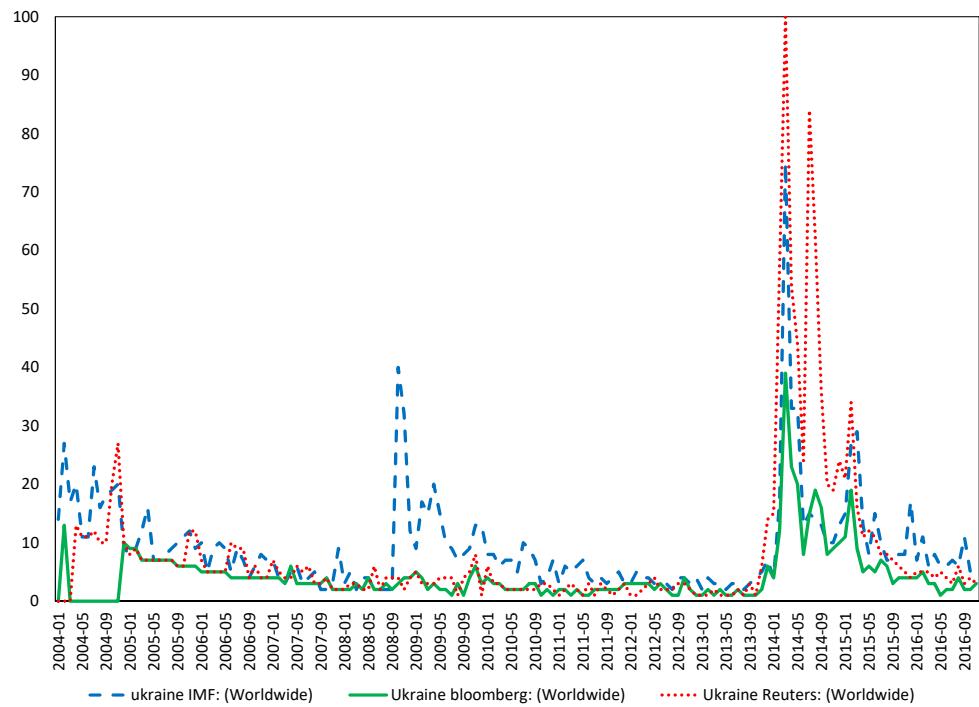


Figure C.3: Benchmark Search Language versus Most Common Alternatives



Blue: English (Benchmark), Yellow: Russian, Red: Chinese