Investor Information and Bank Instability During the European Debt Crisis*

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Abstract

Outside of financial crises, investors have little incentive to produce private information on banks' short-term liabilities held as information-insensitive safe assets. The same does not hold during crises. We compare the information effects of different policy interventions. We measure information production using credit default swap spreads during the Global Financial Crisis and the European debt crisis. We study abnormal information production around major events and find that capital injections reduced abnormal information production while early European stress tests increased it. High levels of information production predict bank balance sheet contraction and higher government expenditures to support financial institutions.

JEL Codes: G01, G20, G21, G28

Keywords: information production, financial crises, safe asset

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1 Introduction

Financial crises are information events when money-like debt becomes information sensitive. Policymakers' crisis-time interventions affect the information environment. Typically, banks' short-term liabilities are information-insensitive safe assets. But when investors produce private information on bank liabilities, financial instability risks build. Information production dynamics before crises reveal growing instabilities and depend on the adequacy and credibility of policymakers' actions. In this paper, we compare different interventions to assess which have the largest effect on the information environment. We empirically estimate daily information production in the context of the European sovereign debt crisis, show the effects of different policies on information production, and link information production to the ultimate cost of a crisis to the taxpayer.[1] We argue that policymakers' information management efforts are first-order important during financial crises, and their choice of intervention should be guided by how effective it is at improving the information environment.

Financial crises occur when the wisdom that bifurcates safe assets from risky assets falters. Safe assets are money-like because they are liquid and provide a store of value. A sovereign can create safe assets, backed by the taxpayer's guarantee, or the banking system can produce them, backed by collateral. Money-like bank liabilities take many forms, including bank deposits, commercial paper, and repurchase agreements. Safe assets are a necessary component of any financial system. Dang et al. (2017) argue that a social planner wants banks' debt to be information-insensitive, so there is little incentive for investors to produce private information on banks' money-like liabilities. When nobody produces private information, everybody has "symmetric ignorance" which eliminates adverse selection risk for uninformed agents (Holmström, 2015).

A real-world example makes the intuition clear: before the Global Financial Crisis, repo backed by asset-backed securities (ABS) were a large source of private safe asset production and a significant source of financing for the banking system. Wholesale creditors took the collateral *no questions asked*, in Holmström (2015)'s phraseology. Creditors were unequipped

[1] The set of European countries included in the analysis is based on the universe of CDS contracts in Markit's "Europe" region. These include: Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Guernsey, Iceland, Ireland, Italy, Jersey, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. As a region, we divide Europe further into the United Kingdom; "periphery" countries, including Greece, Ireland, Italy, Portugal, and Spain; and "core" countries, including the rest.

to perform detailed credit analyses of ABS collateral. They had no incentive to do so.[2] Credit research on safe assets is normally unprofitable because the collateral is far from bankruptcy. That creditors accept collateral backing money no questions asked is an essential feature of safe assets. But as creditors grew weary of ABS collateral quality—because of information production—repo haircuts increased, amounting to a run on the banking system. Turmoil in collateralized financing markets returned to a semblance of normality only after an unprecedented intervention by the Federal Reserve. Iorgova et al. (2012) provides a detailed discussion on safe assets and the Global Financial Crisis.

In practical terms, private information acquisition happens when experts do their own costly due diligence and create in-house valuation models. Private information acquisition occurs when experts believe they are better able to understand information compared to the average market participant (Holmström, 2015). Perraudin and Wu (2008), for example, show that before the collapse of two Bear Stearns hedge funds in the summer of 2007, several flavors of asset-backed securities traded at nearly identical prices even though they were backed by different collateral pools. Experts and nonexperts produced no information on them, and market participants referred to a shared set of benchmark indices or credit ratings. But following the two funds' collapse, the prices diverged rather than simply falling. Experts tried to form their own expectations about the individual securities rather than deferring to simple benchmarks.

All financial crisis firefighting policies shape the information environment. Some policies explicitly address information production: short-sale bans, for example. While we do not empirically identify the channels through which interventions affect information production, the likely channels are intuitive. For example, asset purchase programs can set a floor on information-sensitive asset prices. Credible stress tests reduce the incentive for investors to produce private information by making the banking system's exposures and sensitivities common knowledge. Gorton (2008) highlights the channels through which information production ignited the Global Financial Crisis.

To understand the effects of interventions on information production, we create a measure of daily information production. The measure uses the cross-sectional standard deviation of credit default swap (CDS) spreads across financial companies relative to non-financial companies. We term the measure the *information production ratio* (ipr_t). CDS contracts

[2]This paper only covers wholesale creditors and not retail creditors.

pay off when the underlying company defaults, reflecting market expectations of default probabilities. After Lehman Brothers' bankruptcy, ipr_t spikes, falls over the following year, and then spikes again as the European sovereign debt crisis engulfs the continent. Our measure of information production is not just a restatement of average CDS spreads; we show they are uncorrelated.

Essential to our information production measurement is that we control for information production in the non-financial sector because we are interested in bank-specific information production rather than aggregate information production. Information production on both financial and non-financial firms rose through 2008, but the relative change is our primary interest. Relative to its 2006 average, non-financial information production roughly doubled after Lehman's bankruptcy. For financials, information production grew 22 times its 2006 average immediately after Lehman and settled around seven times in the last quarter of 2008. A recession brings higher default probabilities for both financial and non-financial companies, so it is no surprise that information production for both increase during the crisis. But when information production for the financial system grows considerably faster than for the non-financial sector, risks of bank runs and safe asset destruction are high.

We conduct abnormal information production event studies. The event studies allow us to understand which policies or interventions effectively reduce information production. To measure abnormal information production, we first estimate innovations to ipr_t using an AR(1) process, which we denote ipr_t^{Δ}. We conduct information production event studies by testing whether ipr_t^{Δ} is statistically different from zero in the days following an event since $\mathbb{E}[ipr_t^{\Delta}] = 0$ by construction. We run event studies across five types of events: stress tests, capital injections, institution-specific interventions, open market operations and asset purchase programs, and important periphery events. Early European stress tests led to increased levels of abnormal information production for core European countries. In contrast, the 2009 U.S. stress tests led to a substantial decline in abnormal information production. Later stress tests reduced information production for Europe as a whole. The work is similar in spirit to event studies that gauge the effectiveness of stress testing exercises during crises (e.g., Candelon and Sy 2015; Fernandes et al. 2020; and Sahin et al. 2020).

There are myriad differences in the interventions we examine, and only infrequently is there a consistent pattern, suggesting that details are important. As a first-pass estimate, we estimate abnormal information production by intervention type in a panel setting. Averaging across all countries and interventions, we find capital injections and the periphery agreements reduced abnormal information production; other intervention types do not have a statistically significant effect.

We study how investors produce information in the absence of access to adequate information to gauge banks' riskiness. We hypothesize that they use a basket of reference securities as a proxy and apply a shrinkage regression to select a set of reference securities that explains the variation in banks' CDS returns. The reference securities analysis shows that banks' returns covaried strongly with traded securities during both the Global Financial Crisis and the European debt crisis, unlike the pre-crisis period. We test the accuracy of the reference security model with respect to changes in the information production measure (ipr_t^{Δ}). In a vector autoregression setting, we find that information production falls when realized returns exceed the reference security model's expectation. Because the model error is persistent in sign, ipr_t^{Δ}'s subsequent decline is surprising because rational investors should produce information regardless of the residual's sign. We resolve the puzzle by arguing investors are less concerned about the model's outright accuracy and more concerned about tail risk.

In the last part of the paper, we link information production to real outcomes. First, we find that higher levels of ipr_{t-1} predict the subsequent cost to the government of direct intervention in financial institutions at the year-country level. A one standard deviation increase in ipr_{t-1} within a country predicts a 0.6 percentage point increase in costs as a share of that country's GDP the following year.

Finally, we look at European banks and show high levels of information production in year t predict lower bank loans, lower assets, and lower equity the following year. A unit increase in ipr_{t-1} corresponds to a subsequent contraction of gross loans of 1.2 percent, assets of 1.3 percent, and total equity of 1.3 percent after controlling for several bank characteristics.

Related Literature Our work is related to the literature on the relationship between banks' production of private safe assets, information insensitivity, and information production (e.g., Gorton and Pennacchi 1990; Holmström 2015; Dang et al. 2015, 2019; and, Dang et al. 2017). Our paper is most closely related to Chousakos et al. (2020), who measure information production empirically via the cross-sectional standard deviation of equity returns. In a panel setting, they show that higher levels of information at the quarter by country level predict financial crises when productivity growth is low. Our paper is different from theirs in that we are interested in high-frequency changes in information production to evaluate policy interventions and important events, whereas they show that information can be aggregated at a coarser level to forecast financial crises across countries.

2 A Model of Information Production

The information production view of financial crises focuses on the role of information-insensitive securities in an economy. Theoretical work addresses three principal questions: Why are they desirable? Why are they always debt? How do banks make them?

Why are information-insensitive securities desirable? Gorton and Pennacchi (1990) show that information-insensitive assets are necessary because uninformed agents need a transaction medium free of adverse selection. Banks produce information-insensitive assets to satisfy uninformed agents' demand to transact freely with privately-informed agents at stable transaction values.

Why are information-insensitive securities always debt? Dang et al. (2015) present a theoretical model that shows why debt backed by debt collateral is the least information-sensitive asset. Debt-on-debt is efficient because it maximizes trade across agents. If debt collateral values fall, information-insensitive assets turn information-sensitive. Debt issuers counterbalance falling collateral values by overcollateralizing the debt, issuing less debt, or issuing debt at shorter maturities. A bank run occurs when debt issuers cannot offset falling collateral values. A financial crisis occurs when adverse selection risks prevent agents from trading altogether, consistent with empirical evidence on asset-backed commercial paper in 2008 (Covitz et al. 2012), repos in 2008 (Gorton and Metrick 2012), and collateralized-loan obligations during the Covid-19 shock (Foley-Fisher et al. 2020).

How do banks make information-insensitive securities? Dang et al. (2017) argue that banks are endogenously opaque, so they can efficiently produce information-insensitive debt. Gorton (2014) studies the development of opacity in the U.S. banking system and shows that in the early twentieth century, for example, banks remained opaque by preventing information production via equity markets.[3,4] Deposit insurance did not change banks'

[3]Banks accounted for a large share of the New York stock market until 1872 when all banks delisted. Banks also kept their stocks illiquid by issuing only few shares to keep individual stock prices prohibitively expensive.

[4]Gorton (2014) also highlights a 1964 Congressional study of bank opacity and bank equity: "Stockholders of banks in many cases receive little or no information concerning the financial results of their bank's

opacity: Badertscher et al. (2015) show that banks' stock returns respond to *Call Report* disclosures.

We motivate our empirical work via the theoretical approach of Dang et al. (2017), which we modify slightly to examine how policymakers can manage information production during crises when investors monitor reference securities to proxy solvency. Under this approach, banks produce bank money—equivalent to uninsured deposits—most efficiently when they are opaque. Experts cannot create private information about a bank's assets when the bank is opaque, and agents are thus willing to accept bank debt at face value because there is less risk of adverse selection.

The model has three periods, $t \in \{0, 1, 2\}$, and four agents: a firm with an investment project at date $t = 0$ that pays off at $t = 2$; an early consumer with an endowment at $t = 0$ and a liquidity need at $t = 1$; a late consumer with an endowment at $t = 1$; and a bank. The investment project requires a loan at $t = 0$, but the early consumer cannot both fund the project and cover its upcoming liquidity need. The solution is straightforward: the early consumer lends to the firm at $t = 0$, the late consumer fulfills the early consumer's liquidity need at $t = 1$, and the firm and both consumers share the payoff of the project at $t = 2$. However, the two consumers cannot agree to the efficient allocation because the late consumer enters the economy only at $t = 1$. The bank provides the first-best allocation by intermediating between the two consumers.

To offer the first-best allocation, the bank must not reveal details about the investment project—the bank's asset—at $t = 1$ to the late consumer. Otherwise, the late consumer will produce private information about the likelihood of the project succeeding and only lend in good states. Let Ψ represent the late consumer's incentive to acquire private information about the project:

$$\Psi = k - e + \omega - \frac{\gamma}{d} \tag{1}$$

where γ is the cost of monitoring bank assets, d is the probability of the bad state, k is the consumer's liquidity demand, e is the consumer's endowment, and ω is the cost of

operations. Less than 50 percent of all banks publish annual reports. Of those who publish annual reports, 29 percent do not reveal the size of their valuation reserves. Before-tax earnings are not disclosed by 36 percent of all banks and after tax earnings are not disclosed by 34 percent of all banks."

investment in worthy projects.[5] The incentive to produce information is increasing in the cost of productive investment, liquidity need, and the probability of the bad states. The incentive is decreasing in endowments and the cost of monitoring bank assets. Banks implement the first-best allocation when private information acquisition incentives are sufficiently low, corresponding to $\Psi \leq 0$.

Suppose that investors infer the bad state probability using a linear combination of d^a, the probability of a bad state based on actuarial analysis, and d^r, the probability of a bad state based on the reference security, with weight $w \in [0, 1]$:

$$d = wd^a + (1 - w)d^r \tag{2}$$

where $d^r \geq d^a$ as mark-to-market losses often overestimate realized losses. Investors struggle to produce information on the bank's assets because banks only infrequently provide balance sheet details, and disclosures are coarse. We argue that investors instead use reference securities to infer solvency because they have observable prices. Any reference security, however, is fraught with uncertainty. In times of stress, market prices reflect both credit fundamentals and liquidity premia, which are tough to disentangle—assuming that market prices reveal only credit fundamentals would exaggerate losses. Geithner et al. (2022) argue that many investors inferred banks' solvency using subprime mortgage price indices during the global financial crisis.

Combining the previous equations yields:

$$\Psi = k - e + \omega - \frac{\gamma}{wd^a + (1 - w)d^r} \tag{3}$$

Equation 3 establishes a simple framework of the ways in which crisis-related policies can affect information production. Policymakers can reduce incentives to produce information, and thereby increase the likelihood that the bank can implement the first-best allocation. Policy interventions can target four transmission channels, even though some are more expensive or unavailable.

First, policymakers can increase the cost of monitoring the bank ($\gamma \uparrow$): extreme examples of this are the United Kingdom and United States bans on financial stock short-selling in

[5] See Dang et al. (2017), equation 7.

September 2008. Second, officials can reduce investor's beliefs about the reference security's efficacy ($1 - w \downarrow$): examples include policies such as widespread use of funding guarantees (the FDIC's "Debt Guarantee Program") or capital backstops (the U.S. Treasury's "Capital Assistance Program"). Third, policymakers can reduce the probability of the bad state implied by the reference security ($d^r \downarrow$). This can be done via interventions that reduce fire-sales and information production by lowering the liquidity premium, which investors may erroneously infer to be equivalent to solvency—a mistake so long as the bank remains a going concern. For example, Ashcraft et al. (2012) show that the Federal Reserve's Term Asset-Backed Securities Loan Facility improved ABS liquidity. Fourth, policymakers can reduce the actuarial probability of the bad state ($d^a \downarrow$). The fourth channel is harder to target with any specific policy and depends on the broader economic context.

3 Measuring Information Production

We measure daily information production using the cross-sectional standard deviation of credit default swap (CDS) spreads for the senior unsecured debt of financial companies relative to non-financial companies. We term this new measure the *information production ratio* (ipr_t). CDS spreads reflect market expectations of default probabilities since a CDS contract pays off when the company defaults and is, in effect, insurance against default. Senior debt is designed to be more information-insensitive than equity. Compared to equity, senior unsecured debt has lower payoffs because the debt pays off in most states of the world. As Dang et al. (2017) indicate, in low payoff states (e.g., during crises), senior debtholders have limited incentives to acquire information since they are contractually paid back first and, hence, are exposed to the lowest expected losses. In the model's language, the probability of a bad state d and the incentive to acquire private information Ψ are low. The face value of senior debt is highly stable—in fact nearly flat—as long as the firm remains away from bankruptcy. It is usually more profitable to produce information to inform speculation in equities than in senior unsecured debt. Holmström (2015) notes that equity is designed for risk-sharing and is therefore information-*sensitive*, allowing for price discovery. Equity is traded on centralized exchanges with continuous analyst coverage; neither is true for senior debt.

We use euro-denominated five-year CDS contracts—the most liquid tenor—for senior, unsecured debt on non-government entities with modified-modified restructuring (MM and MM14) clauses, the most common contract type in Europe. We use MM contracts before September 22, 2014 and MM14 contracts after, following convention. All data is sourced from Markit. To control for changes in the composition of firms with traded CDS contracts, we require that a firm has a full year of CDS spreads reported in 2006. After these cuts, our resulting sample has 1.3 million day-firm observations, of which financials are 415,000. We use analogous data for the U.S. sample, except we use dollar-denominated contracts with modified-restructuring clauses (MR and MR14), the most common contract type in the U.S. CDS markets are more mature in the U.S., so we also require that the contract has a Markit rating. Non-rated contracts constitute a much larger share of the data in the United States relative to European countries, and their spreads are not available consistently from day to day.

We do not use CDS contracts for senior secured debt because the data are sparse: only 19,000 observations for financials, with only 12 data points available before 2007. If we drop the requirement that a firm has a full year of observations in 2006, we can calculate an information production ratio for senior secured debt. However, the smaller sample size is a severe limitation—most CDS trading occurs in senior contracts referencing unsecured debt. For example, in our sample of senior unsecured CDS there are, on average, 230 non-financial firms compared to the senior secured sample's 9 firms. For financials, the comparison is 103 financial firms compared to 7. Even so, the information production ratios for senior secured and unsecured in Europe are positively correlated with a correlation coefficient of 0.22.

We drop six firms with outlier spreads from the U.S. CDS sample: PMI Group Inc, Ambac Financial Group, MBIA Insurance, Financial Guaranty Insurance, Ambac Assurance, and Rouse Co. Except for Rouse, these companies provide insurance for municipal bonds or mortgages, so their CDS spreads remain extremely volatile well after the crisis because they often depend on litigation outcomes. These companies' general behavior matches many other financials' CDS spreads during the early stages of the financial crisis. For example, in 2014 MBIA sought damages from JP Morgan, as the successor of Bear Stearns, for misrepresenting the quality of securitizations that Bear Stearns had underwritten with insurance backing from MBIA. Our benchmark measure of information production does not materially change if we instead set the spreads of these six firms to a constant after their spike up in the initial stages of the crisis, to mute the effect of subsequent litigation and regulatory action well after the crisis.

In addition to the CDS data, we use price and return data from Bloomberg, bank-specific balance sheet information from Fitch, and Treasury yield data from FRED. We use a standardized business calendar based on the dates with unique Treasury yield observations to determine trading days and set returns relative to these days. While information is certainly produced on trading holidays and weekends, we implicitly assume that markets reflect this information on the next trading day. Indeed, policymakers likely use non-trading days to help smooth information production during especially volatile periods or important announcements, allowing the market to digest the news.

To calculate information production, we first calculate the cross-sectional standard deviation of CDS spreads across financial companies on a given day, denoted $\sigma_{t,Financials}$:

$$\sigma_{t,Financials} = \sqrt{\frac{1}{n}\sum_{i}(CDS_{i,t} - \overline{\mu}_{i,t})^2} \tag{4}$$

where $\text{CDS}_{i,t}$ is the CDS spread for financial company i, n is the number of financial companies in the sample, and $\overline{\mu}_{i,t}$ is the average CDS spread across all financial companies, all on day t, with no weighting. An equivalent measure for non-financial companies is $\sigma_{t,Non-financials}$. We define the information production ratio, ipr_t as the cross-sectional standard deviation within financial companies divided by the identical measure for non-financial companies:

$$ipr_t = \frac{\sigma_{t,Financials}}{\sigma_{t,Non-financials}} \tag{5}$$

The non-financial companies included in our sample represent a diversified sample of more than 300 firms across several sectors and countries. The most common sectors include industrials (19 percent e.g., BAE Systems), consumer goods (19 percent e.g., Unilever), consumer services (17 percent, e.g., Tesco), utilities (17 percent, e.g., Enel), and basic materials (11 percent, e.g., UPM-Kymmene Oyj). Firms also come from telecommunications, energy, healthcare, and technology. The non-financial companies come from 17 different European countries, with the U.K., France, and Germany the most common. Non-financial firms have higher CDS spreads, implying they are modestly riskier. CDS spreads for financials are lower than non-financials by roughly 0.2 percentage points on a simple unweighted basis.

We cannot directly measure Ψ, the incentive for agents to acquire private information on banks. Instead, we associate the output of information production with observed changes in relative CDS spreads, ipr_t^{Δ}. Specifically, we assume that Ψ_t is affine in ipr_t:

$$\Psi_t = a + b(ipr_t) \tag{6}$$

Following He et al. (2017), we estimate innovations to ipr_t based on the residual from an AR(1) process estimated from daily data from 2006 through 2014: $ipr_t = \rho_0 + \rho ipr_{t-1} + u_t$. We convert the innovations to a growth rate as:

$$ipr_t^{\Delta} = u_t / ipr_{t-1} \tag{7}$$

Our ipr_t measure controls for information production relative to the non-financial sector because we are interested in the relative change in new information specific to the banking system. When information production for the banking system grows considerably faster than for the non-financial sector, the risks of bank runs and safe asset destruction are high.

3.1 Evolution of Information Production

Figure 1 plots ipr_t and ipr_t^{Δ}. Information production ipr_t spiked after the Lehman Brothers' bankruptcy, then fell in the intervening years, and spiked again at the onset of the European debt crisis. Pre-crisis, the average level of information production ipr_t in 2006 was about 0.6 (red line in Figure 1). It jumped to 5.6 on October 7, 2008, shortly before the United Kingdom unveiled its capital injection plan. After falling in the ensuing years, the ipr_t jumped again in 2011 to a local maximum of 2.9 in February 2011, shortly after Fitch Ratings downgraded Greek sovereign debt to junk.

Information production rose through 2008 as the crisis unfolded and economies slowed. Yet information production in the financial sector ($\sigma_{t,Financials}$) grew 22 times its 2006 average immediately after Lehman to settle at around seven times at end-2008, but only doubled in the non-financial sector, as shown in Figure 2.

We can slice the data to make more granular ipr_t measures, although smaller slices are subject to larger measurement error. Figure 3 shows the ipr_t for continental Europe, the United Kingdom, the periphery (Greece, Ireland, Italy, Portugal, and Spain), core Europe (excluding the United Kingdom and the periphery), and the United States.

In Figure 3, the United Kingdom's ipr_t spiked in late 2008 and 2009 and stabilizes at a level triple the pre-crisis average. The periphery ipr_t remained low in the initial stages of the Global Financial Crisis but spikes in early 2011. In the core, ipr_t spiked dramatically in October 2008 but remains low at all times, except for a blip in late 2011. The United States ipr_t broadly followed the United Kingdom with a spike in 2008 and another in 2010 before slowly recovering.

Table 1 provides the average, standard deviation, and extrema for ipr_t, ipr_t^{Δ}, $\sigma_{t,Financials}$, and $\sigma_{t,Non-financials}$. Because the average $\sigma_{t,Non-financials}$ is larger than the average $\sigma_{t,Financials}$, the average ipr_t across the regions is always less than one. The average information-production ratio is broadly similar across countries ranging from 0.5 to 0.9. The periphery region has the largest volatility in the ipr_t, but the United States has the largest volatility of ipr_t^{Δ}.

Table 2 shows the correlation across region-specific ipr_t^{Δ}. The Europe-wide ipr_t^{Δ} is correlated at the 5 percent level with all other regions' ipr_t^{Δ}. Both the United States and the United Kingdom covary strongly with the periphery, whereas neither covaries with the core Europe.

Three important properties of the ipr_t measure are worth noting. First, as a measure of the relative dispersion of the CDS spreads of financial and non-financial companies, the ipr_t permits discriminating information production during financial crises from that during episodes of adverse real shocks. Such differentiation of financial and real shocks is in line with findings in the literature, such as Muir (2015) who finds that, in equity markets, risk premia rise considerably more during financial crises than during other types of events, including economic recessions.

Second, the cross-sectional variation in CDS spreads increases in bad states as the average CDS spread rises. In principle, this does not hold under all circumstances. If investors believe a recession is uniformly bad news for all companies, the dispersion in spreads should remain low, even as the average spread increases. In this case, investors do not produce private information. Alternatively, if investors believe there will be winners and losers, spreads will reflect these differences as investors produce information. We find support for the latter hypothesis. Table 3 regresses changes in $\sigma_{t,Financials}$ on changes in average financial companies' CDS spreads in the first five columns: every region has a strong positive relationship between average financial spreads and the cross-sectional variance of these spreads. In bad states, investors differentiate between strong and weak banks. The last five columns show the same regression but change the dependent variable to ipr_t^{Δ}: each region has a positive significant relationship between changes in average bank CDS spreads and innovations to the information-production ratio.

Third, the information production ratio ipr_t is a novel measure and not a restatement of average CDS spreads, the market return, or other common cyclical measures. Figure 4 shows the time series compared against average financial CDS spreads. Regressing ipr_t on CDS spreads shows no statistically significant relationship. We also show that ipr_t^{Δ} is not explained by other common market stress measures in Table 4. We find no statistically significant relationship between ipr_t^{Δ} and changes in the European VIX, the 10-year Spanish-Bund spread, the Bloomberg European Financial Conditions index, the slope of the overnight to three-month Libor curve, and the Libor-OIS three-month spread. The table also shows no relationship between ipr_t^{Δ} and the S&P 350 Europe, the FTSE100, the S&P 500, or bank equity indices for continental Europe, the United Kingdom, and the United States.

Sophisticated institutional market participants are most likely the beneficiaries of information production, although we cannot directly measure their benefit. We argue that sophisticated investors benefit more than retail investors in two ways: first, CDS markets are limited to specialized traders who face large financial fixed costs for data and market access. Moreover, the average trade is well beyond the dollar amount retail traders could commit: Chen et al. (2011) find that the average CDS trade size is roughly \$5 million for single-name CDS.

Empirically, we find that information production coincides with net outflows from institutional money market funds, not retail money market funds. While such evidence is not conclusive, it is consistent with sophisticated investors, not retail investors, benefitting from information production. We use data on U.S. money market mutual fund flows from Schmidt et al. (2016) who provide aggregated daily net assets and net flows across several types of money funds. We focus on prime institutional and prime retail funds, both large types of money market funds that clearly delineate institutional investors and retail investors. For each type of money fund, we regress date t's flows (as a share of the previous day's total net assets) on the previous day's ipr_{t-1}^{Δ}:

$$\text{Money Fund Flows}_t = \alpha + \beta ipr_{t-1}^{\Delta} + \gamma X_t + \varepsilon_t$$

where *Money Fund Flows* is calculated for either prime institutional or prime retail funds. X_t is a vector of controls including additional lags of ipr^{Δ}_{t-1}, flows from the fund, the level of net assets (in million dollars), and monthly fixed effects. The sample is daily from January 2, 2008 to June 30, 2009. Flow shares are multiplied by 100 to make the coefficients interpretable as percentage points.

Table 5 shows the regression results. The first three columns show the result when running the regression using daily flows in prime institutional funds, and the last three show the results using prime retail funds. ipr^{Δ}_{t-1} has a significant and negative coefficient only for institutional money fund flows across all specifications. The effect is weakly negative but much closer to zero and not statistically different from zero for retail funds. A one-standard-deviation increase in ipr^{Δ}_{t-1} (0.12) corresponds to net outflows the following day of roughly \$1 billion for prime institutional funds, using the coefficient in column (3) and the peak prime institutional net asset value of \$1.3 trillion. Such results are consistent with institutional investors benefitting from information production rather than retail investors.

3.2 The Information Production Ratio Captures Firm-Specific Information Production

Our key identifying assumption is that increases in the dispersion of financial firms' CDS spreads, relative to the same measure for non-financials, are positively related to firm-specific information production. One concern is that the dispersion across CDS spreads increases without any information production. This is clear if we consider a simple single factor model of CDS spreads:

$$CDS_{i,t} = \alpha_i + \beta_i X_t + \varepsilon_{i,t} \tag{8}$$

The dispersion in CDS spreads will increase if either X_t or $\varepsilon_{i,t}$ increases, holding betas fixed. This is a problem since we are interested in information production captured in $\varepsilon_{i,t}$, rather than mechanical variation that comes from X_t. Untangling the two components is difficult since we do not know firm-specific betas.

Instead, we confirm that ipr_t captures firm-specific information production ($\varepsilon_{i,t}$) by using Campbell et al. (2001)'s decomposition to estimate the average firm-specific volatility of CDS spreads for financial companies. The advantage of their approach is that we do not need to estimate firm-specific betas: Campbell et al. (2001)'s decomposition depends on the identifying assumption that the average firm-specific beta to a market factor is 1.

Our identifying assumption is similar to Campbell et al. (2001). We redefine the market factor as the universe of financials with CDS spreads. Our key identifying assumption is that the average financial's beta to this financial market factor is 1. The disadvantage to redefining the market factor is that we cannot estimate average industry volatility, as Campbell et al. (2001) does. In Table 6 we verify this assumption by estimating each firm's CDS beta by year, and then averaging across these year-by-firm beta estimates. We take averages of year-by-firm beta estimates rather than firm beta estimates over the full sample because some firms enter and exit the sample over time. The first column of the table shows that the mean financial firm beta to the financial market index is 0.95, and the median is 1.05. We formally verify that the betas are close to 1 by running a t-test, and the p-value of 0.83 indicates that we cannot reject the null that the underlying average financial firm beta is different from 1. For comparison, the second column of the table shows the analogous data for non-financials' beta to the financial market index. Non-financials have somewhat higher betas on average, and the p-value of 0.00 shows we can reject the null that the average non-financial firm has a beta equal to 1.

Let s denote the interval at which spreads are measured and let t denote the interval over which we estimate volatility. We use daily CDS spreads over weekly intervals. We define the market as the universe of all financials with CDS spreads. We estimate the sample volatility of all financial firms' CDS spreads at weekly intervals from daily data, which we term FINMKT_t:

$$\text{FINMKT}_t = \sum_{s \in t} \left(CDS_{m,t} - \mu_m \right)^2$$

where $CDS_{m,t}$ is the average spread across all financial firms on date t and μ_m is the mean market CDS spread over the sample s.

We estimate firm-specific volatility in two steps. First, we calculate the firm-specific residual $\eta_{i,t}$ (see Campbell et al. (2001) Eq. 10):

$$\eta_{i,t} = CDS_{i,t} - CDS_{m,t}$$

Second, the average firm-level volatility, FINFIRM_t, is the equal-weighted average of firm-specific volatilities

$$\text{FINFIRM}_t = \frac{1}{N}\sum_{i\in N}\sum_{s\in t}\eta_{i,t}^2$$

Our method differs from Campbell et al. (2001)'s in that we are interested in average firm-level volatility within financial companies, so we treat the universe of financial firms as the market. We also follow the convention with CDS indices of equal-weighting spreads rather than using market-capitalization weights.

We plot the volatility of the universe of financials' CDS spreads (FINMKT_t) on the left panel of Figure 5, and we plot the average firm-specific volatility (FINFIRM_t) on the right panel. Both measures are visually cyclical, with a dramatic spike in the fall of 2008 and increases in late 2011 and early 2012. Like Campbell et al. (2001), our estimate of average firm-specific volatility is considerably higher than the volatility of the aggregate financials market. Since we are focused on senior unsecured debt it is unsurprising that, on average, both volatility measures are lower than Campbell et al. (2001)'s volatility estimates for equities.

We run a horserace to confirm that ipr_t captures firm-specific volatility and is not spanned by the aggregate financial system's volatility. We regress ipr_t on FINMKT_t and FINFIRM_t in Table 7. We standardized the independent variables to have zero mean and unit variance to make the coefficients easier to compare. The first four columns regress the level of the information production (ipr_t) on levels of volatility, and the last four regress the AR(1) innovations of information production (ipr_t^{Δ}) on changes in volatility estimates. The fourth and eighth columns give regression estimates after winsorizing the independent variables at the 5 percent and 95 percent thresholds to reduce the influence of the outliers in the fall of 2008.

In both level and difference terms, ipr_t and ipr_t^{Δ} are highly correlated with average firm-specific volatility as estimated by FINFIRM_t. In columns (2) and (3) we can see that even though both the firm-specific and market-wide volatility estimates are positively correlated with ipr_t, the coefficient on firm-specific volatility is roughly four times larger. Moreover, ipr_t is not significantly positively correlated with the aggregate market volatility estimated by FINMKT_t in level terms or differences.

4 Results

4.1 Abnormal Information Production and Policy Responses

Event studies have been used widely as a tool in finance and economics. We now extend this tool to the study of *abnormal* information production around times of various policy responses. This provides important quantitative insights on the effect of such policy responses on information production. The event studies are run across five types of policy events: stress tests, capital injections, institution-specific interventions, open market operations and asset purchase programs, and important country-specific events. There is considerable heterogeneity in the abnormal information production across the types of interventions we examine. We therefore estimate abnormal information production by intervention type and also average across all countries and interventions.

Specifically, we test information production by comparing the average ipr_t^{Δ} in the five days after the event, including the day itself, relative to the average ipr_t^{Δ} on all other days in the sample using:

$$ipr_t^{\Delta} = \alpha + \beta \mathbb{I}(\text{Event}_t) + \theta_t + \varepsilon_t \tag{9}$$

where $\mathbb{I}(\text{Event})$ is an indicator variable equal to 1 if the date t is in the five days following the event, and 0 otherwise, and θ_t are year fixed-effects. The null hypothesis is that the event creates no incentive for markets to cumulatively produce information over the following five days, so $\sum_{t=1}^{5} ipr_t^{\Delta} = 0$. However, $\beta > 0$ reflects increased average information production, and $\beta < 0$ reflects a decrease. We run the test separately for each region: Europe, core Europe, periphery Europe, the United Kingdom, and the United States. Since we estimate ipr_t^{Δ} as the residual from an AR(1) process, $\mathbb{E}[ipr_t^{\Delta}] = 0$ over the full sample. Empirically, the average Europe-wide ipr_t^{Δ} is indeed nearly zero at -0.006 over the full sample, but the average varies from year to year: 0.027 in 2011 and -0.039 in 2014. Since we are specifically interested in the effect a single intervention on information production as opposed to the broader context of the intervention, we add year fixed-effects to ensure the identified effect is not errantly picking up a trend in ipr_t^{Δ}. We carry out event studies both for individual events and by intervention type.

Implicit in the test is an assumption that markets digest news about interventions within five days. The assumption is standard in the event study literature and using different horizons does not qualitatively change our results. However, our test differs from other event studies because we have no cross-section: we are only able to compare ipr_t^{Δ} in the time-series. Moreover, the reality of financial crises is that interventions are lumpy—they often occur in rapid succession. It is not possible to separately identify different policies that occur within the same five-day window. In this respect, we treat our results estimated in September and October 2008—a period of many successive interventions—as subject to higher measurement error than other policies isolated on the calendar.

Our analysis of abnormal information production suggests that while the 2009 U.S. stress test was associated with a large decline in information production, the effect of the European stress tests between 2009 and 2012 was not as definitive. Conversely, other types of interventions—including capital injections, institution-specific interventions, open-market operations, and asset purchase programs—were found to be significant in compressing abnormal information production in continental Europe (both in its core and periphery) but not in the United Kingdom and the United States.

Table 8 gives the average abnormal information production test results for U.S. and European stress tests. The results yield two conclusions. First, the 2009 U.S. stress test—broadly viewed as credible—was associated with a large decline in information production following both its announcement (−5.4 percent) and results (−12.1 percent). An average daily ipr_t^{Δ} of −12.1 percent corresponds to an approximately 60 percent cumulative reduction in information production. This constitutes the largest reduction for the U.S., and the third-largest effect we find across all regions, following only the impact of the U.S. bank capital injection on the European core (−17.7 percent) and the ECB's August 2011 bond purchase program (−14.6 percent).

Second, the European stress tests between 2009 and 2012 did not have an effect similar to that of the U.S. test. The 2010 and 2012 tests had statistically significant effects Europe-wide (−2.3 percent and −2.1 percent, respectively). Yet the aggregate number likely obscures heterogeneity in information production across member states. The 2010 and 2012 tests were associated with large reductions in information production the periphery (−3.9 percent and −3.7 percent) but saw large increases in the core (1.9 and 9.8), while the United Kingdom was flat and ipr_t^{Δ} fell in the United States following the 2012 test only. Moreover, the 2012 Europe-wide test announcement in December 2011 coincided with the ECB's announcement of the 3-year Long-Term Refinancing Operations.

The heterogeneity in information production across European countries during the stress tests is not surprising. For example, six out of the seven banks in the 2010 European stress test that did not meet the 6 percent hurdle rate were from periphery countries.[6] The banks under 6 percent included three cajas and two private banks from Spain, one Greek bank, and one German bank. Industry commentary supports the narrative of heterogeneity across regions. van Steenis et al. (2010) note that:

> The one positive is that the country that needed most to deliver credible results—Spain—has managed to do a lot better than its peers . . . All else being equal, the relatively worse disclosure from core country banks argues for a tightening of core-periphery spreads, although given the detailed sovereign risk exposures that have been released by most banks (with some notable exceptions in Germany), it is now easier for market analysts to perform their own sovereign stress tests.

Investors likely produce information about individual banks and groups of closely related banks, given they have similar exposure to shocks (Jorion and Zhang, 2007). For example, investors often grouped investment banks during the Global Financial Crisis: especially Bear Stearns, Lehman Brothers, Merrill Lynch, and Morgan Stanley. Such groupings would introduce an omitted variable bias into equation 8. Policymakers likely endogenously respond to such groupings as they craft interventions. For example, the initial U.S. capital injection in 2008 focused on only nine financial institutions.[7] Similarly, policymakers explicitly grouped banks in the stress tests. For example, the 2009 SCAP stress test focused on the 19 largest banks, those with more than $100 billion in assets.

As another example, the Federal Reserve announced both Morgan Stanley and Goldman Sachs could become bank holding companies on the same day on September 21, 2008. The announcement certified that the Federal Reserve would be their supervisor and provided them with potential access to the discount window. Had the Federal Reserve announced only one of the two banks could become a bank holding company, the market could have inferred that as a signal about the health of one versus the other. Interventions that respond

[6] The 2010 European stress test included 91 banks and found seven banks with a Tier 1 ratio below a 6 percent, 24 banks below 7 percent, and 39 below 8 percent.

[7] These banks included Bank of America, Bank of New York Mellon, Citigroup, JP Morgan Chase, Morgan Stanley, State Street, Wells Fargo and Merrill Lynch.

to such groupings may be more potent but pose a challenge to empirically test given their endogenous design.

Table 9 provides results on abnormal information production associated with capital injections, institution-specific interventions, open-market operations and asset purchase programs, and important events related to the periphery. For the two capital injections we test—the October 2008 U.K. and U.S. injections— there is a large negative point estimate for almost all regions, but the effect is only significant for core Europe and periphery. The failure of Lehman Brothers in 2008 had a large positive effect on core Europe but no effect in the United States, likely because information production in the United States occurred earlier, prior to the event window. The FSA and SEC's bans on stock short-sales had a large positive effect on abnormal information production in all regions except the periphery, suggesting that information production in CDS markets continued. However, we should interpret the results in the context of the rapid sequence of events in the week following September 19, 2008. The intervention in Fortis and the Congressional approval of TARP occurred on the same day, so the large negative effect in the United States and the United Kingdom is not specific to either intervention.

Open-market operations and asset-purchase programs have mixed results. The August 2011 ECB purchase program of Italian and Spanish bonds had a large negative effect, while TALF and QE had a somewhat smaller, but still significant, reduction in information production. In the U.S., BNP's suspension of redemptions from its subprime funds and the initial August 2007 liquidity provision led to a large increase in information production of 12.6 percent.

Periphery interventions are mostly uniformly good for reducing information production. Information production fell after each deal— Greece in May 2010 and July 2011, Ireland in November 2010, and Portugal in May 2011—although the effect is only significant in the 2010 interventions.

Overall, information production after seemingly similar interventions varies widely—it is not easy to say which of broad invention type is the most effective by scanning the rows of Tables 8 or 9. This suggests that particular types of interventions (e.g., stress tests) should not be viewed as a fail-safe tool to reduce information production. The different outcomes of the U.S. and early European tests also point to the need for a more detailed study of the specific facets of the two exercises that may explain the relative success of the earlier.

The devil is ultimately in the details: the institutional context, market expectations, and idiosyncratic features of the interventions play at least as large a role in managing information production as the broad type of intervention.

As a first-pass estimate, we estimate an aggregated event study to measure abnormal information production by intervention type, presented in Table 10. The test is identical to previous tests, except rather than isolating a single event we instead set $\mathbb{I}(\text{Event}) = 1$ for the five days following all of the events of that type. The first five columns show the average abnormal information production following events of a particular type within a region, and the last column shows the average across the panel of all areas.

Capital injections and policy responses that targeted the periphery reduced abnormal information production, but other intervention types did not have a statistically significant effect. Capital injections lead to an average reduction of -4.7 percent across all countries, and the effect is larger in continental Europe (-9.5 percent) and smaller, but still significant, in the United Kingdom (-0.9 percent). While not significant for continental Europe as a whole, the periphery events had a negative effect for the United Kingdom, the United States, and the full sample. Notably, excluding the "bad" periphery events (the Greece December 2009 debt announcement and the escalating fears in September 2011) yields broadly larger reductions in information production across all regions.

An important caveat is that the panel regression ignores many aspects of the interventions—idiosyncrasies or design features—which cannot be controlled or measured in this step-up. But the results support our hypothesis that details of the interventions are of first order of importance and that no intervention occurs in a vacuum: it must be credible, respond to market expectations, and depend on the institutional context of the action.

4.2 Testing the Reference Security View of Crises

While ipr_t^{Δ} measures the level of abnormal information production—in terms of changing CDS spread dispersions—we now study how investors produce information on banks. Investors cannot distinguish the riskiness of different banks because they do not have bank-specific information, or this information may be insufficiently granular. We hypothesize that in this case markets use a basket of reference securities to proxy a bank's solvency and that this basket should that explain most of the variation in banks' CDS returns. The optimal reference securities are identified from a set of candidate securities using a least absolute shrinkage and selection operation (LASSO) regression. The regression finds the best descriptors of a panel of bank CDS returns over a period including the Global Financial Crisis and the European debt crisis.

While ipr_t measures Ψ_t in equation 3, we now test the reference security model in which investors infer the probability of a bad state from a portfolio of reference securities because they do not have detailed or up-to-date information on bank exposures. Specifically, we argue that the investors infer the probability of a bad state d^r in equation 3 from some linear transformation of a portfolio of banks' CDS spreads:

$$\Delta d_t^r = \gamma_0 + \gamma_1 r_t^{CDS} \tag{10}$$

where r_t^{CDS} is the return on a portfolio of bank CDS, and investors choose a set of N reference securities with returns $r_{1,t}^{\text{ref}}, r_{2,t}^{\text{ref}}, \ldots, r_{N,t}^{\text{ref}}$ to estimate the daily returns of a bank CDS position:

$$r_t^{CDS} = \alpha + \beta_1 r_{1,t}^{ref}, + \beta_2 r_{2,t}^{ref} \cdots + \beta_N r_{N,t}^{ref} + \varepsilon_t \tag{11}$$

This set-up assumes that markets use a basket of reference securities to proxy a bank's solvency, implying that the same basket should price the cross-section of banks' returns. Our choice of functional form is motivated by the literature on pricing the cross-section of asset returns via affine multifactor models, including Fama and French (1993), Adrian et al. (2014), and He et al. (2017).

Running an OLS regression of bank CDS returns on dozens of candidate reference securities is problematic. First, OLS estimates have large variance despite their low bias when the number of possible explanatory variables is large relative to the time dimension. Second, we are not interested in the specific securities per se but in identifying a subset of securities that explain most of the variation in banks' returns to interpret in an economic sense investors' perception of bank failures. We approach the problem by identifying such securities using a shrinkage regression based on daily data to ensure a sufficiently large time dimension.

From a set of candidate reference securities, we identify the most descriptive reference securities using a LASSO to find the best descriptors of a panel of bank CDS returns. We identify the optimal model using a 10-fold cross validation approach. The cross-validation process estimates the model on different subsamples to see which selection of explanatory variables is most robust in consistently explaining bank CDS returns. We separately run the LASSO on a pre-crisis sample (before June 1, 2007), a global financial crisis sample (June 1, 2007, to July 1, 2009), and a European debt crisis sample (July 1, 2009 to April 1, 2014), because we expect the basket of reference securities changes as financial stresses change.

The dependent variable in the LASSO is a panel of short CDS returns (i.e., selling protection) for financial companies by translating CDS spreads to returns. Specifically, we translate CDS spreads to returns using

$$r_{i,t}^{CDS} = -1 \times \left(\frac{CDS_{i,t-1}}{250} + \Delta CDS_{i,t} \times RVPV01_{t-1} \right) \tag{12}$$

where t denotes day t, i denotes company i, $RVPV01$ is the risky present value of one basis point calculated using a linearly interpolated Euribor swap curve, and CDS_t is the CDS spread.

The 27 candidate reference securities—the independent variables in the LASSO—are:

- *Equity*: S&P 350 Europe, Euro Stoxx 50, FTSE 100 (United Kingdom), CAC 40 (France), DAX (Germany), IBEX 35 (Spain), FTSE MIB (Italy), PSI All-Share (Portugal), ISEQ Overall (Ireland), ASE General (Greece);

- *Real Estate*: S&P Europe Property (includes companies involved in leasing buildings and dwellings, mini-warehouses and self-storage units, real estate development, real estate property managers, and real estate rental and leasing), S&P Europe REIT (not available during the pre-crisis period);

- *Sovereign Bonds*: Bloomberg-Barclays All Bonds Total Return indices for Germany, Greece, Ireland, Italy, Portugal, and Spain;

- *Exchange Rates*: EURUSD, GBPUSD;

- *Fixed Income*: iBoxx Euro Collateralized Overall, iBoxx Euro Overall, iBoxx Corporate BBB, iBoxx Corporate AAA;

- *CDS:* iTraxx Europe five-year which measures the total return of funded long-credit position in the on-the-run iTraxx Europe five-year index; and

- Monoline Insurers: Syncora, MBIA.

All indices are total return indices and converted to euro-denominated terms if not originally denominated in euros. American equity returns, the monolines, are lagged by one day to reflect timing differences.

We list the summary statistics of the reference securities across the pre-crisis, Global Financial Crisis, and European Crisis stages in Table 11. Unsurprisingly, equities and real estate have large returns during the pre-crisis period and fall during the Global Financial Crisis. During the European debt crisis, average returns are positive for most asset classes, but the standard deviation of daily returns is larger for almost all reference securities.

Figure 6 plots the betas of the model-selected optimal portfolio of reference securities that have an absolute beta value greater than 0.01. Pre-crisis, the iTraxx has the largest beta (0.10) and the iBoxx BBB is the only other indicator with a meaningfully large beta (0.08). Because we examine the cross-section of bank CDS returns, the iTraxx index is the CDS equivalent of a market factor. The selected reference securities in the Global Financial Crisis period still include the iTraxx (0.57, roughly six times its pre-crisis beta), iBoxx BBB (0.87), and other reference securities have much larger betas now: iBoxx AAA (0.07), Greek sovereign bonds (0.06), and German bunds (-0.66). The reference securities for the global financial crisis reflect concerns about the real economy—both highly- and lowly-rated bonds—as well as stresses in the periphery (Greece), and the hedge value of Bunds. During the European debt crisis, Spanish and Irish sovereign bonds (0.04 and 0.02, respectively) grow in importance. The iBoxx AAA's beta shifts from 0.08 to -0.20, and the Bund beta attenuates to -0.07.

We include several reference securities that reflect general economic conditions even if investors do not use them to produce information on banks because bank CDS returns likely covary with both undiversifiable systemic risk and bank-specific reference securities. Other reference securities likely reflect specific line-items that likely have a direct impact on bank health (e.g., Greek bonds or collateralized debt).

In particular, we include the iTraxx which is equivalent to a CDS market factor, similar to the S&P500 for U.S. equities. The LASSO results shows that both matter: in each sample period, the iTraxx index is the first or second most important explanatory variable. However, the LASSO shows that several more granular indices matter even after controlling for the market indicator, especially those related to real estate and equity or bond returns in countries undergoing stress. These other indicators likely proxy for the performance of individual banks' assets, but sufficiently granular exposure data is not publicly available to estimate banks' exact exposures. In a different but related setting, Chodorow-Reich et al. (2021) show that life insurers' market equity value have low betas to the market value of their assets outside financial crises, but that beta grows increases to 1 during the Global Financial Crisis. We find a similar result when comparing the betas of the reference securities over the different samples, and both are consistent with increased information sensitivity of the underlying firms.

We test the accuracy of the reference security model with respect to ipr_t^{Δ}. After the LASSO selects the reference securities for each sample, we estimate the model on bank CDS returns using a growing-window rolling regression to estimate CDS returns, $r_{i,t}^{\text{CDS}}$ and obtain the predicted returns, $\widehat{r}_{i,t}^{\text{CDS}}$. We then calculate the average model residuals by averaging across all company-specific residuals on a given day t:

$$\bar{\varepsilon}_t = \frac{1}{N}\sum_{i=1}^{N}\left(r_{i,t}^{CDS} - \hat{r}_{i,t}^{CDS}\right) \tag{13}$$

The average residual reflects the model's accuracy across all companies, as well as whether realized returns outperform ($\bar{\varepsilon}_t > 0$) or underperform ($\bar{\varepsilon}_t < 0$) the counterfactual expected by the basket of reference portfolios. Finally, we make a time-series of residuals by splicing the residuals estimated by the Global Financial Crisis model and the European sovereign debt crisis model.

We estimate a two-variable vector autoregression model using the model residuals and innovation to the Europe-wide information-production ratio over the crisis sample, June 2007 to April 2014:

$$\begin{bmatrix} ipr_t^{\Delta} \\ \bar{\varepsilon}_t \end{bmatrix} = \mathbf{a_0} + \mathbf{A_1}\begin{bmatrix} ipr_{t-1}^{\Delta} \\ \bar{\varepsilon}_{t-1} \end{bmatrix} + \cdots + \mathbf{A_{t-k}}\begin{bmatrix} ipr_{t-k}^{\Delta} \\ \bar{\varepsilon}_{t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \tag{14}$$

where $\mathbf{a_0}$ is a vector of intercept terms and $\mathbf{A_1}, \ldots, \mathbf{A_{t-k}}$ are 2×2 matrices of coefficients of on lags of ipr_t^{Δ} and $\bar{\varepsilon}_t$. We include 15 trading-day lags, k. Because the VAR uses the LASSO model residual—that is, the residual is the CDS return above and beyond what the reference securities would suggest—the residual should be unrelated to general economic indicators precisely because the indicators are included as part of the reference securities.

Figure 7 plots the cumulative orthogonalized impulse response functions. The left panel shows the effect of an impulse on the model residual on ipr_t^{Δ}, the middle panel shows the effect of an ipr_t^{Δ} impulse on the model residual, and the last panel shows the effect of an impulse on the residual on the subsequent residual. An impulse to the model residual when the model is pessimistic relative to realized returns leads to a reduction in information production. Because the model error is persistent in sign, ipr_t^{Δ}'s subsequent decline is surprising because rational investors should produce information regardless of the residual's sign. We resolve the puzzle by arguing investors are less concerned about the model's outright accuracy and more concerned about tail risk.

4.3 Information Production, Bank Outcomes, and Real Outcomes

In the final piece of our empirical work, we relate ipr_t to outcomes in terms of the cost of financial institution interventions to governments and banks' balance sheet dynamics.

We regress country-specific lagged ipr_{t-1} on the net cost of government interventions to support financial institutions, as calculated by Eurostat:

$$\text{Cost/GDP}_{i,t} = \alpha + \beta_1 ipr_{i,t-1} + \beta_2 ipr_{i,t-1}^2 + \varepsilon_{i,t} \tag{15}$$

where i denotes the country and t is year. The independent variable is the demeaned and lagged information production rate for country i. $\text{Cost/GDP}_{i,t}$ is the net cost to country i's government from its interventions to support financial institutions as share of the country's 2008 nominal GDP. A negative net cost corresponds to net revenues. The cost data reflect only the direct costs to the general government from activities specifically undertaken to support financial institutions, without taking into account broader economic stimulus packages. $\mathbb{I}$(Periphery) is a dummy variable equal to 1 if the country is Greece, Ireland, Italy, Portugal, or Spain, and 0 otherwise. Figure 8 gives a scatter plot of the two variables.

To make the linear term coefficient easier to interpret we center ipr_{t-1} to represent the rate of change in cost-to-GDP when ipr_{t-1} is equal to its mean (if we do not demean, the linear term would reflect the rate of change when $ipr_{t-1} = 0$, which is outside the empirical range of ipr_{t-1}). The sample includes 14 countries, each with eight years of observations.[8]

[8] We are limited to countries with a sufficiently rich cross-section of CDS spreads for financial and non-financials because we use country-specific ipr_{t-1} rather than region-specific. The 14 included countries

Column one of Table 12 shows a positive correlation between the centered ipr_{t-1}, although the effect is not significantly different from zero. Including a squared centered term, ipr^2_{t-1}, shows the effect is exponential. Because Ireland is an outlier, we include country fixed-effects in the fourth column, and the effect is still significant and positive. The magnitude is economically significant. The standard deviation of ipr_{t-1} is 0.95, so an ipr_{t-1} one standard deviation above average predicts a cost of financial intervention in the next year of 0.6 percent of GDP.

We use Fitch bank balance sheet data for bank-specific analysis. The data are limited to euro area countries, on a consolidated basis, with semiannual reporting based on the IFRS, and exclude central banks, state and government banks, as well as supranational banks. We keep only the 500 largest banks based on their asset rank in the first half of 2007 and also require banks to have the following variables of interest: total assets, total equity, common equity, operating return on average assets, operating return on average equity, net income, pre-provision profits, provisions, gross loans. The dependent variables of interest are the log difference in total funding, gross loans, total assets, and total equity. The independent variables (all lagged by one semiannual period) are ipr_t, total assets, total equity to assets, return on average equity, provisions to pre-provision profit, and income to assets. We winsorize all variables at the 5 and 95 percent level to reduce the influence of outliers. We also include country and bank fixed-effects and multiply the variables by 100 to make the coefficients easier to interpret.

Table 13 shows the result from regressing Europe-wide ipr_{t-1} and bank balance sheet variables. It shows when ipr_{t-1} is one unit higher, roughly equal to one standard deviation, funding falls the next semiannual period by 1.2 percent, gross loans by 1.2 percent, total assets by 1.3 percent, and total equity by 1.3 percent. The coefficients show that a higher ipr_{t-1} implies banks, on average, delever as assets fall faster than equity. However, the ipr_{t-1} leads to a form of capital adequacy generally viewed as undesirable: shrinking bank balance sheets lead to contraction of credit to the real economy and a host of negative externalities associated with balance sheet contraction.

are: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

4.4 Impact of Covid-19

We calculate ipr_t in Europe and the United States similarly, except now we require companies to have a reported CDS spreads each day of 2019 and 2020 through August 2020.[9] Figure 9 shows the fundamental fact that Covid-19 did not begin as a financial crisis. In March 2020, the cross-sectional variance across non-financial companies increased dramatically. Amid the continued Covid-19 crisis, the levels remain elevated. Unlike the 2008 financial crisis, the spark for the Covid crisis was outside the banking system, and ipr_t fell in the United States and Europe. By August 2020, the cross-sectional standard deviation of non-financial companies was roughly 10 times its level at the beginning of the year, whereas financials were only 13 percent higher.

5 Conclusion

Information production is first-order important for crisis-time policymakers. We show how to use information production as a tool for quantitative ex-post policy evaluation, as an ex ante indicator of crisis, and as a predictor of adverse subsequent real outcomes for the banking system and the associated cost of a crisis to the taxpayer.

We measure daily information production using the cross-sectional standard deviation in financial companies CDS spreads relative to non-financial companies. With a focus on Europe during the Global Financial Crisis and subsequent European debt crisis, we empirically measure the effect of important crisis interventions and news on abnormal information production. We find that the devil is in the details; no specific type of intervention uniformly reduces information production, but capital injections and the periphery country agreements reduced information production on average.

We examine the role of reference securities in driving information production during crises, where investors use a portfolio of traded securities to infer bank health. Information production falls only when the reference securities are too pessimistic, which we argue indicates investors' primary concern is downside risk to the banking system rather than outright model accuracy. Finally, we show that high ipr_t forecasts higher costs to the government of financial interventions and bank balance sheet contraction. After the outbreak of Covid-19, we show

[9] We also exclude Norske Skogindustrier ASA from our European sample as its data is unrealistically volatile.

that the ipr_t fell considerably, reflecting the fundamentally non-financial nature of the shock.

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6 Figures

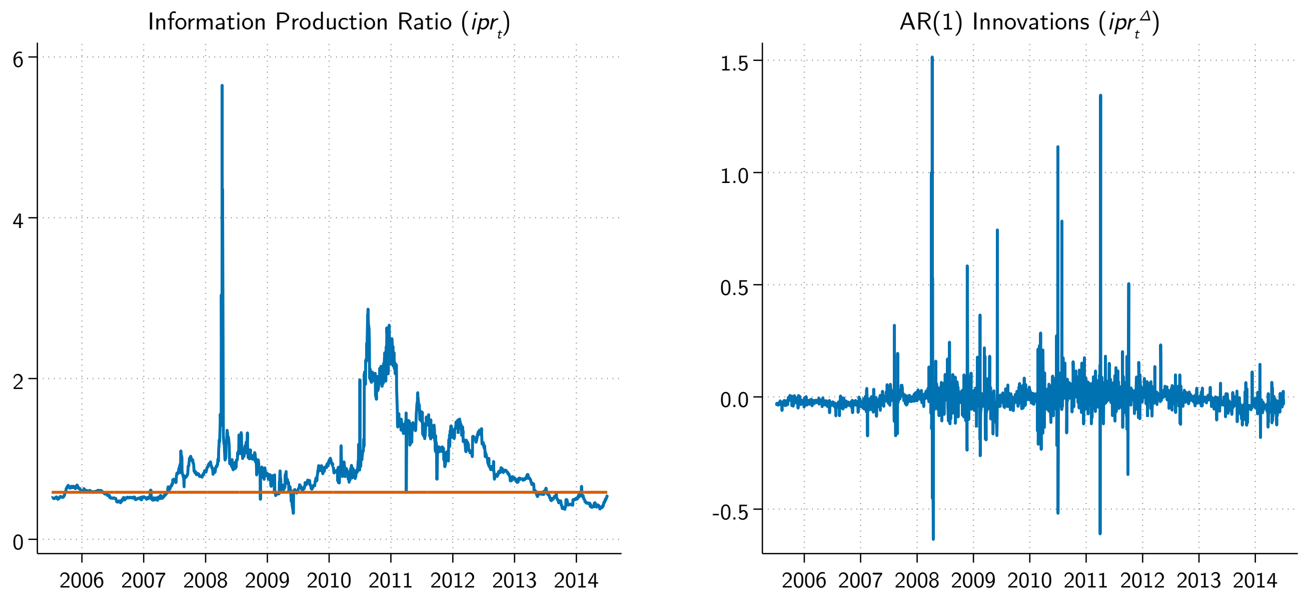

Figure 1: Information Production Ratio in Europe: Level (ipr_t) and Innovations (ipr_t^{Δ}). We plot the "information production ratio," ipr_t, on the left and the innovations to ipr_t, ipt_t^{Δ}, on the right. The red line on the left panel is the average level of ipr_t in 2006, pre-crisis. ipr_t is the daily cross-sectional standard deviation of 5-year euro-denominated senior secured debt CDS spreads within financial companies divided by the same measure within non-financials, excluding government reference entities.

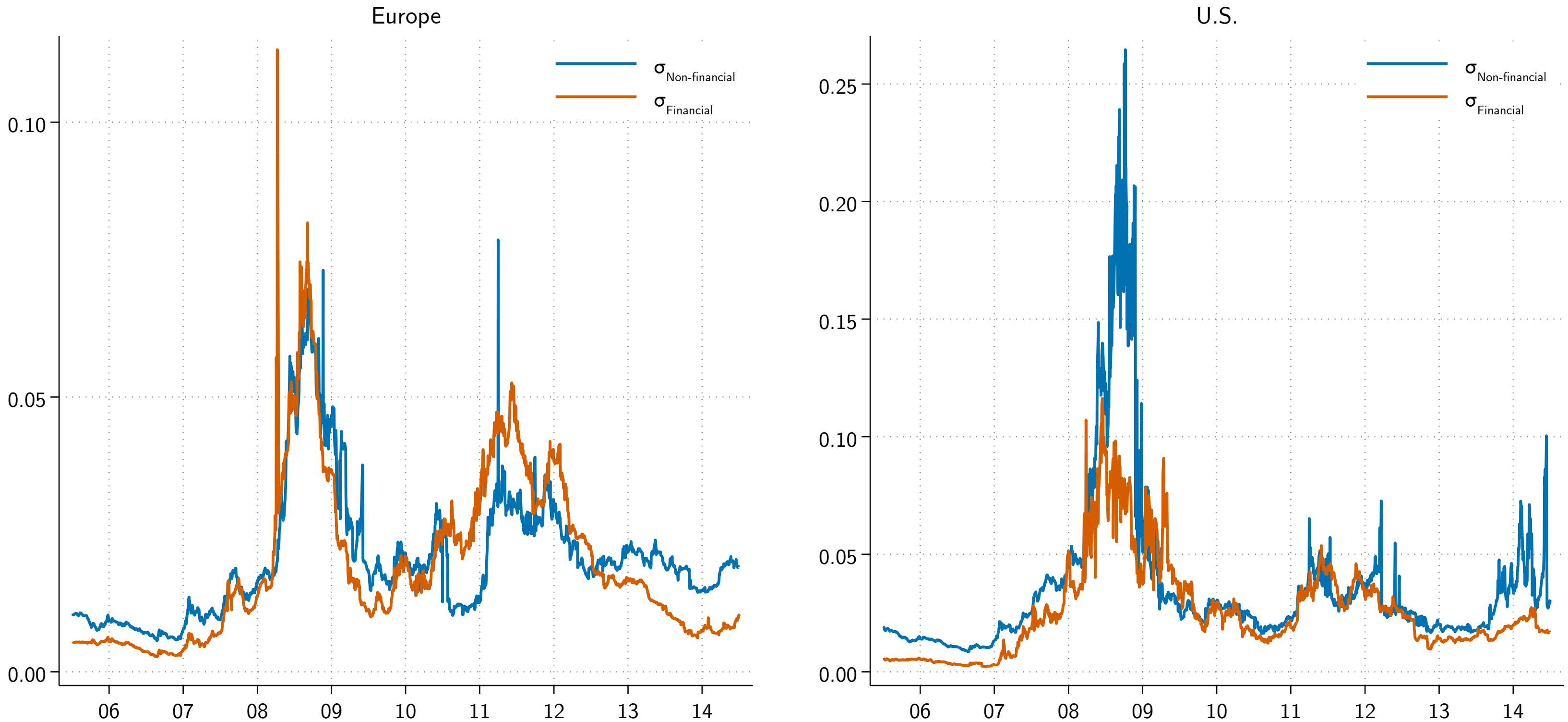

Figure 2: Time series of $\sigma_{Financial}$ and $\sigma_{Non-financial}$. Plot compares the Europe-wide cross-sectional standard deviation of CDS spreads in Europe and in the U.S.

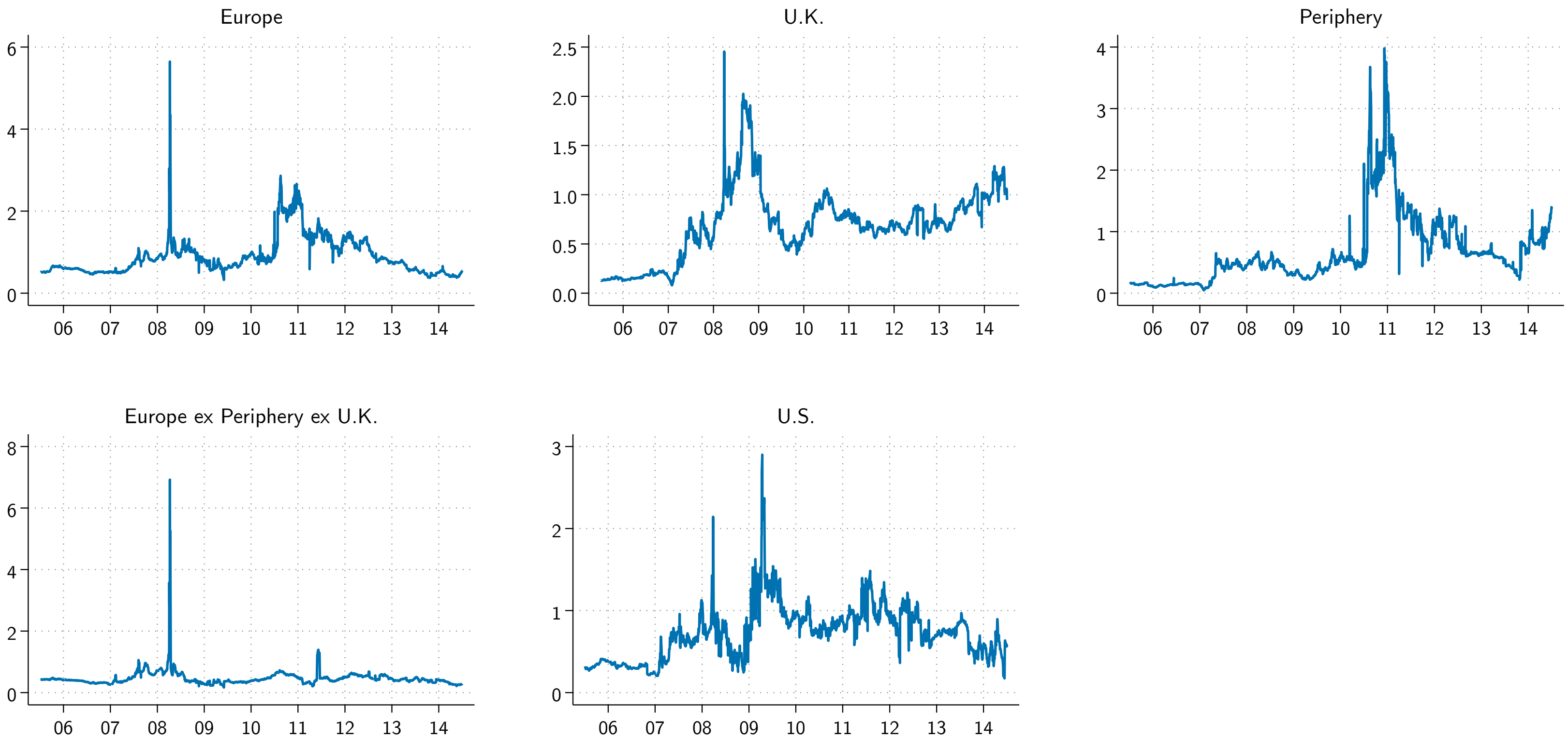

Figure 3: Information Production Ratio Across Countries. We plot the "information production ratio," ipr_t, by country using the same methodology as the aggregate European ipr_t; the U.S. measure a few different cleaning steps, which are described in section 3. ipr_t is the daily cross-sectional standard deviation of 5-year euro-denominated senior secured debt CDS spreads within financial companies divided by the same measure within non-financials, excluding government reference entities, within a region.

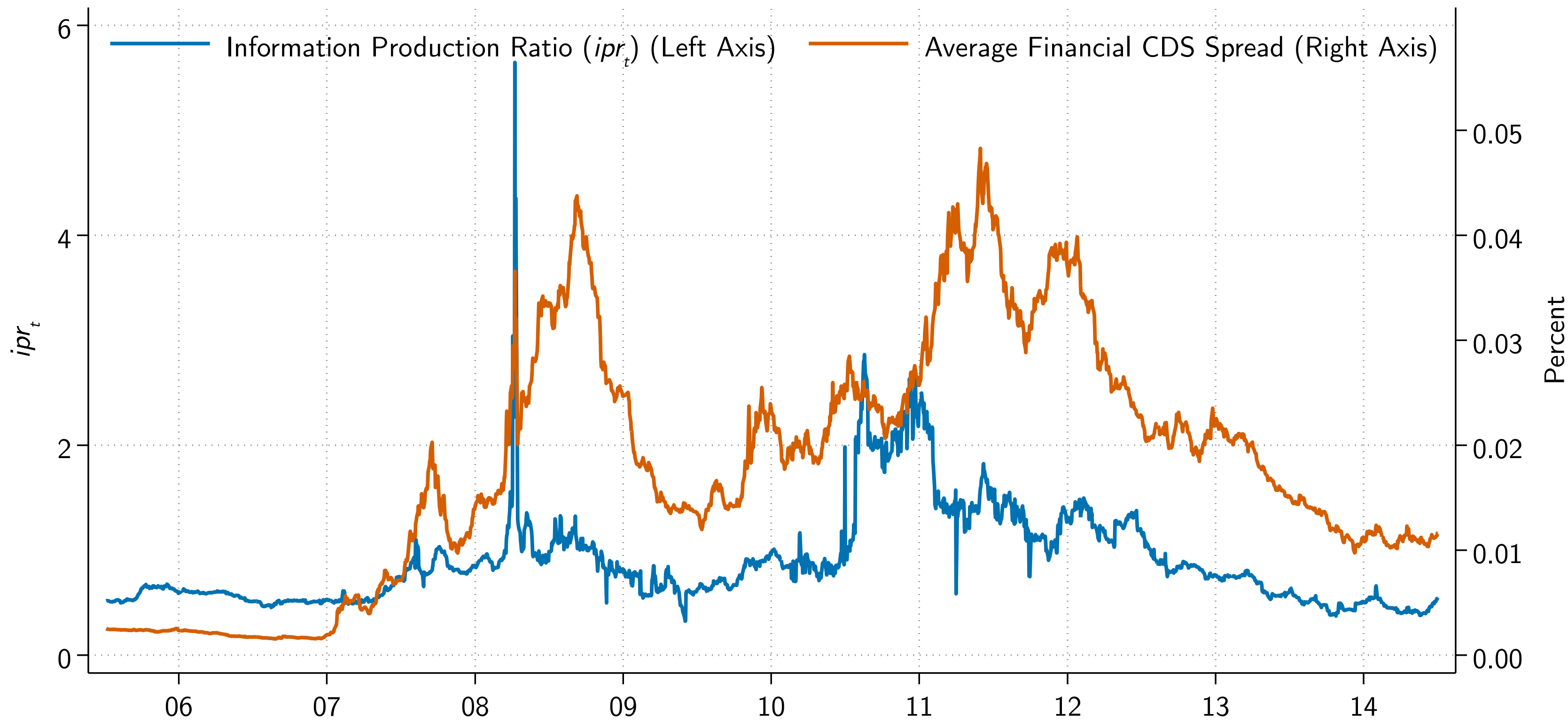

Figure 4: Information Production Ratio vs. Average Financials' CDS Spread. Plot compares the Europe-wide ipr_t vs. European financials' average CDS spread.

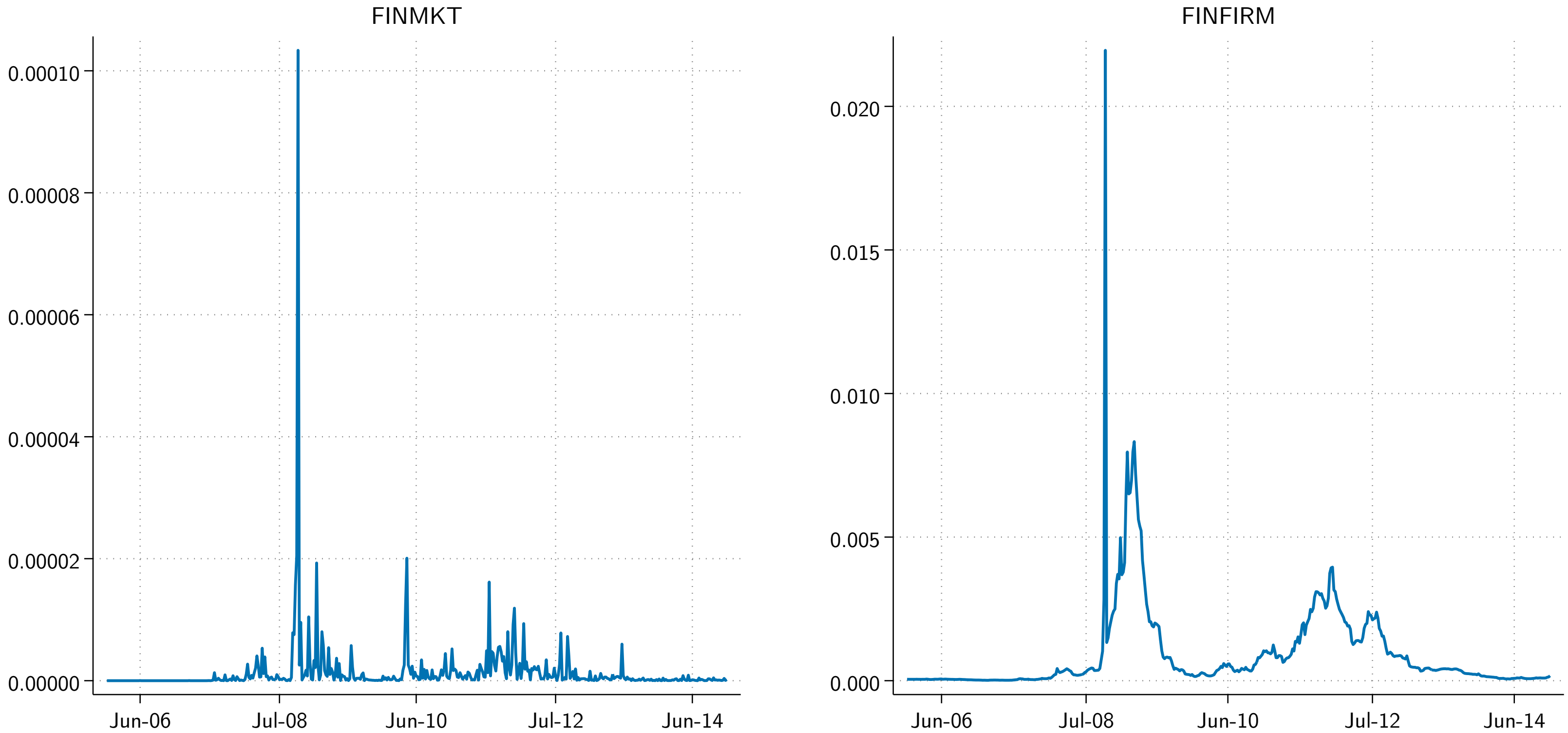

Figure 5: Market and Firm Volatility for Financials. Figures plots estimates of aggregate volatility across all financials' CDS spreads (FINMKT) and average firm-specific volatility (FINFIRM) following Campbell et al. (2001)'s methodology.

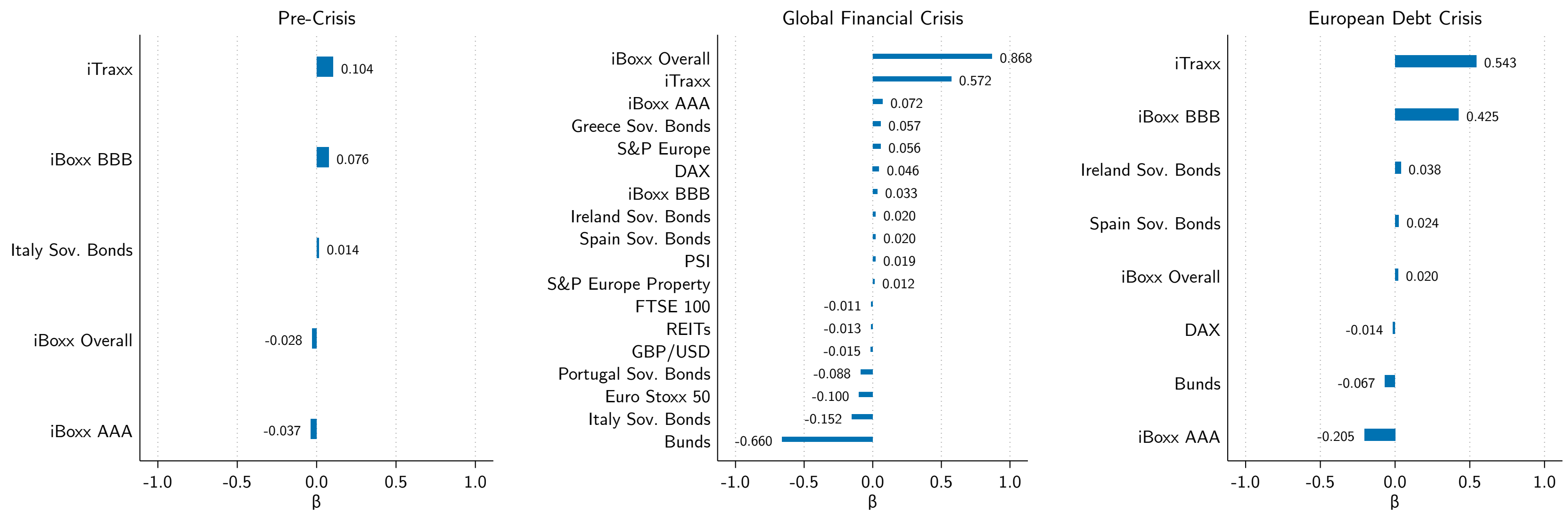

Figure 6: Reference Securities' Betas. Plot gives the betas of the LASSO-selected reference securities which best explain the cross-section of European bank CDS returns over the pre-crisis (before June 1, 2007), Global Financial Crisis (June 1, 2007 to July 1, 2009) and European sovereign debt crisis (August 4, 2009 to April 10, 2014). We plot securities with $|\beta| > 0.01$. All reference securities are in euro-denominated return terms. Bunds is the Bloomberg Barclays total return German sovereign bund index; iBoxx AAA and BBB is the overall total return for AAA-rated and BBB-rated bonds; EUR/USD is the exchange rate; S&P European Property is the total return on S&P's property index which includes companies involved in leasing buildings and dwellings, mini-warehouses and self-storage units, real estate development, real estate property managers, and real estate rental and leasing; ASE is the Athens Stock Exchange index; ISEQ is the Ireland Stock Exchange index; IBEX is the IBEX 35; PSI is the Portuguese PSI-20; sovereign bonds refer to total returns in the Bloomberg Barclays total return index for the respective country; iTraxx is the European iTraxx 5-year index, a portfolio of liquid CDS contracts.

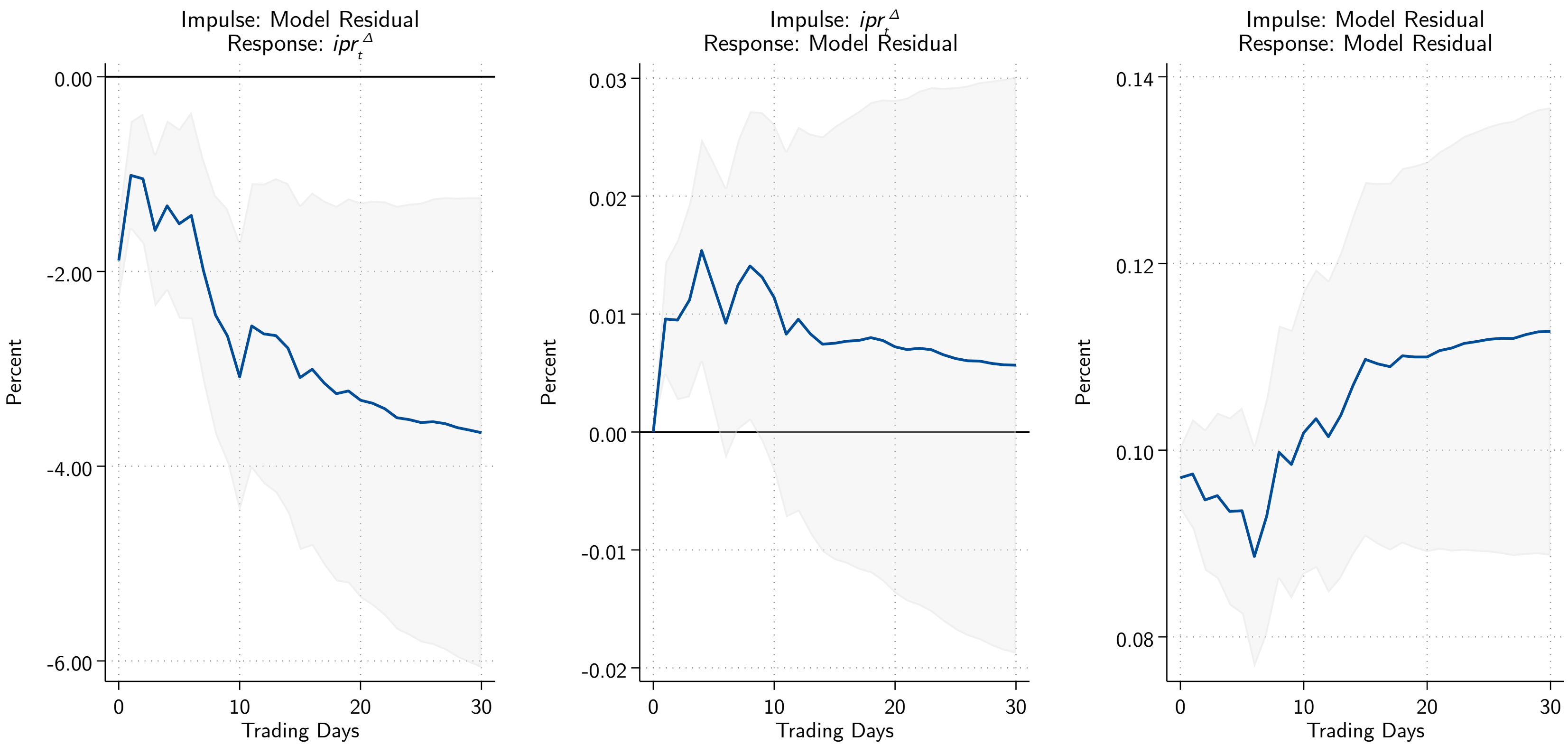

Figure 7: Vector Autoregression Impulse Responses. Plots show cumulative orthogonalized impulse response functions after we estimate a two-variable vector autoregression model using the model residuals and innovations to the Europe-wide information production ratio over the crisis sample, June 2007 to April 2014, described in equation 14. The VAR includes the information production ratio ipr_t and the average model residual across all firms on day t, $\bar{\varepsilon}_t$. We calculate the model residual using the LASSO-selected reference securities and splice the residuals for the Global Financial Crisis and European sovereign debt crisis together.

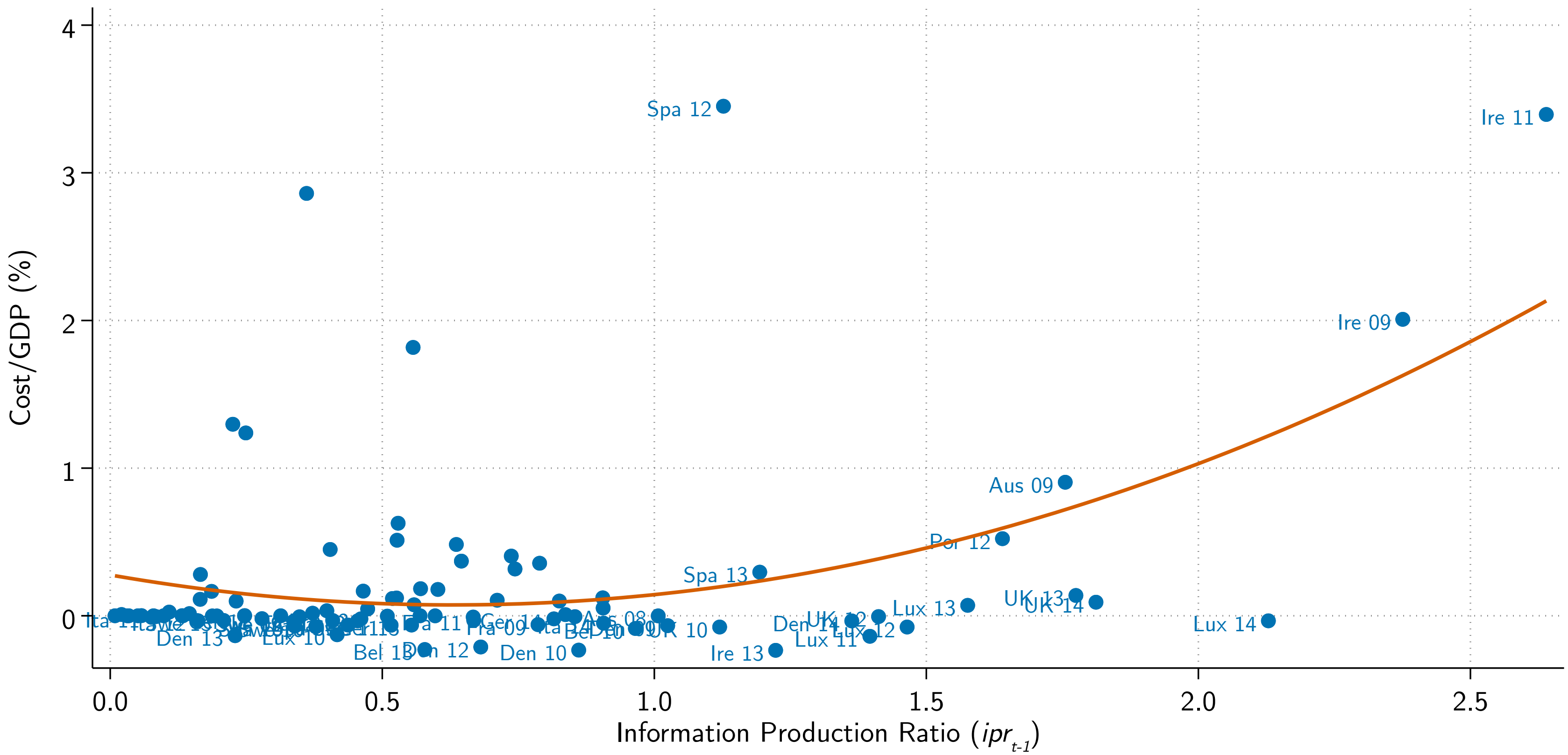

Figure 8: Information Production Ratio Predicts Subsequent Cost of Government Interventions in Financial Institutions. Figure plots country-level ipr_{t-1}, which is lagged at an annual level, and the net cost to the government from government interventions to support financial institutions. A negative net cost is net revenues. Cost data is from Eurostat, and only "to activities undertaken to support financial institutions . . . it does not include wider economic stimulus packages."

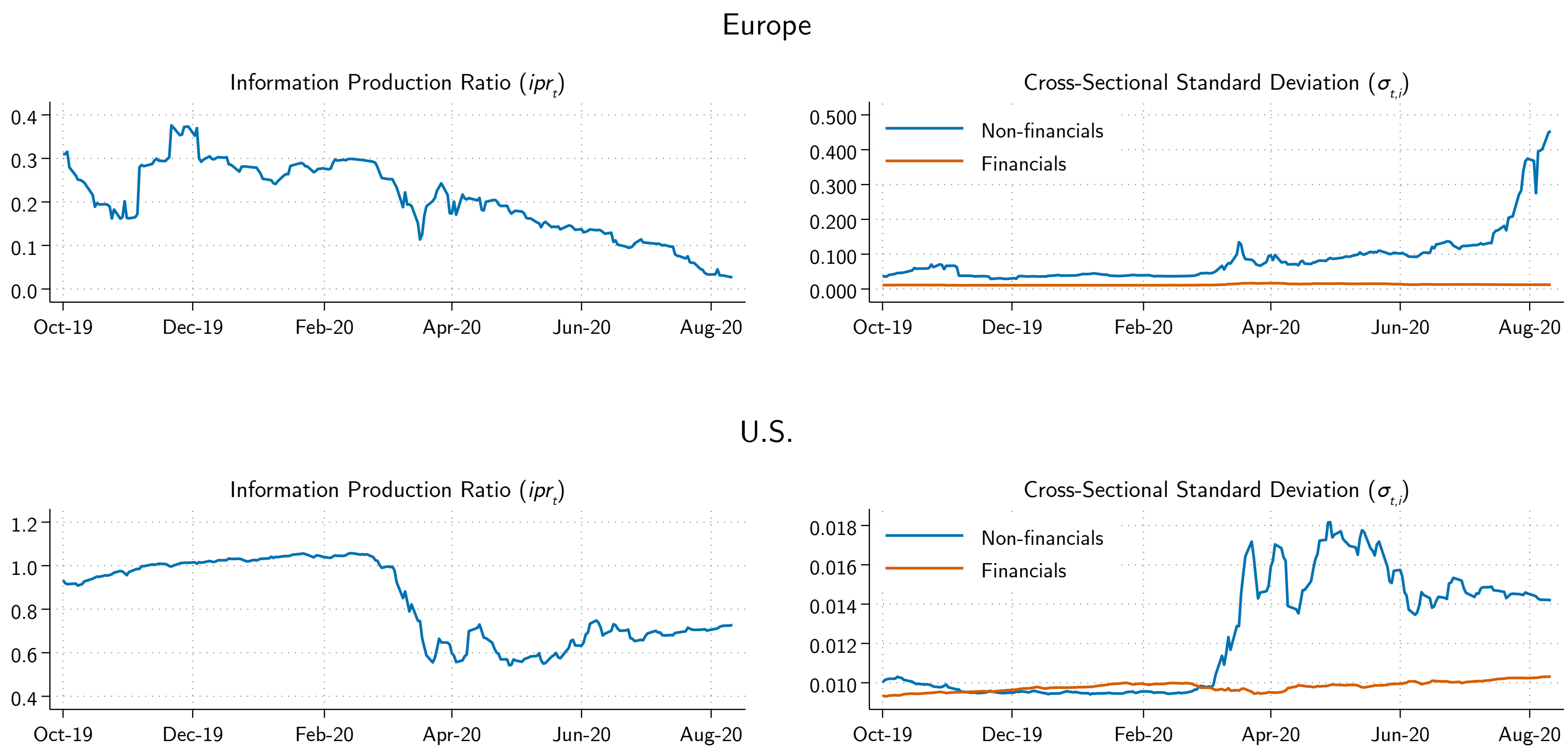

Figure 9: Information Production Ratio During Covid-19. We plot the "Information Production Ratio," ipr_t, using the same methodology as the previous work except we fix the sample of included companies by requiring companies to have CDS spreads every day of 2019 and 2020 through August 2020.

7 Tables

	ipr_t				$ipr_t^{\Delta} \times 100$			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Europe	0.90	0.47	0.32	5.65	−0.61	8.08	−63.47	151.49
Core	0.47	0.27	0.17	6.92	−0.28	4.60	−37.82	51.31
Periphery	0.66	0.58	0.05	3.98	−1.84	10.15	−67.36	186.94
U.K.	0.69	0.37	0.08	2.45	−0.34	12.63	−53.33	246.20
US	0.73	0.33	0.17	2.90	−1.19	14.16	−80.33	341.05

	$\sigma_{t,Financials} \times 100$				$\sigma_{t,Non-financials} \times 100$			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Europe	1.94	1.51	0.27	11.32	2.06	1.19	0.56	7.86
Core	0.71	0.86	0.08	5.12	0.89	0.52	0.37	3.61
Periphery	1.01	0.86	0.19	15.29	2.20	1.44	0.67	9.46
U.K.	1.96	1.88	0.04	7.66	2.69	1.78	0.40	21.86
U.S.	2.57	2.03	0.22	11.63	3.62	3.50	0.86	26.46

Table 1: Information Production Ratio Summary Statistics. Summary statistics for ipr_t and ipr_t^{Δ} for Europe and individual regions. σ terms are the daily cross-sectional standard deviation of financial or non-financials. See section 3 for the calculation details. Data is daily from 2005 to 2014.

	Europe	Core	Periphery	U.K.	U.S.
Europe	1.00				
Core	0.57***	1.00			
Periphery	0.61***	0.04*	1.00		
U.K.	0.05**	0.02	0.08***	1.00	
U.S.	0.06***	0.01	0.04*	0.07***	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Correlation of Region-Specific Information Production Ratio Innovations, ipr_t^{Δ}. Daily data from 2006 through 2014.

	$\Delta\sigma_{t,Financials}$					ipr_t^{Δ}				
	Europe	Periphery	Core	U.K.	U.S.	Europe	Periphery	Core	U.K.	U.S.
$\Delta\overline{CDS}_{financials}^{Europe}$	3.24**					48.31**				
	(1.22)					(17.76)				
$\Delta\overline{CDS}_{t,financials}^{Periphery}$		0.73***					10.36**			
		(0.08)					(4.43)			
$\Delta\overline{CDS}_{t,financials}^{Core}$			4.39***					59.96***		
			(0.77)					(7.25)		
$\Delta\overline{CDS}_{t,financials}^{UK}$				0.63***					13.63*	
				(0.12)					(7.22)	
$\Delta\overline{CDS}_{t,financials}^{US}$					2.22***					31.99***
					(0.21)					(5.85)
Observations	2,252	2,252	2,252	2,252	2,252	2,252	2,252	2,252	2,252	2,252
R^2	0.56	0.38	0.81	0.24	0.63	0.19	0.06	0.38	0.05	0.13

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Cross-Sectional Variance of Financials' CDS Spreads Increase as Average Financials' CDS Spreads Increase. $LHS = \alpha^i + \beta^i(\Delta\overline{CDS}_{t,financials}^{i}) + \varepsilon_t^i,\ \ i \in$ {Europe, U.S., etc} where LHS is either the change in the cross-sectional standard deviation of financials within a country $\Delta\sigma_{t,Financials}$ or ipr_t^{Δ}. Sample from 2006 through 2014. Standard errors clustered by quarter and shown in parentheses. Yearly fixed-effects.

	(1) $R^{S\&P\ Europe}$	(2) $R^{FTSE100}$	(3) $R^{S\&P500}$	(4) $R^{Euro\ banks}$	(5) $R^{UK\ banks}$	(6) $R^{US\ banks}$
ipr_t^{Δ}	−0.00	−0.00	−0.01	0.01	0.00	−0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	2,253	2,253	2,253	2,253	2,253	2,253
R^2	0.00	0.00	0.00	0.00	0.00	0.00

	(1) Δ(Euro VIX)	(2) Δ(Spain-Bund)	(3) Δ(Fin. Conditions)	(4) Δ(3m EUR Libor-EONIA)	(5) Δ(3m EUR Libor-OIS)
ipr_t^{Δ}	−0.12	−0.02	0.04	0.07	0.01
	(0.60)	(0.02)	(0.07)	(0.05)	(0.01)
Observations	2,252	2,252	2,252	2,252	2,252
R^2	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Correlation with Cyclical Measures. Regression run on daily data from 2006 through 2014. Δ(Euro VIX) is change the Euro Stoxx 50 implied volatility; Δ(Spain-Bund) is the change in the spread between 10 year Spanish and German bonds; Δ(Fin. Conditions) is the change in the Bloomberg Euro-zone Financial Conditions; Δ(3m EUR Libor-EONIA) is the change in the slope of the 3-month/overnight spread; Δ(3m EUR Libor-OIS) is the change in the 3-month EUR Libor and 3-month EUR OIS; $R^{SP\ Europe}$ is the S&P Europe 350 index; $R^{FTSE100}$ is the FTSE 100 index; $R^{Euro\ banks}$ is the Euro Stoxx bank index; $R^{UK\ banks}$ is the FTSE 350 bank index; and $R^{US\ banks}$ is the BKX bank index. Standard errors are reported in parentheses using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure.

	Prime Inst. MMFs			Prime Retail MMFs		
	(1)	(2)	(3)	(4)	(5)	(6)
ipr^{Δ}_{t-1}	-0.78^{*}	-0.62^{*}	-0.63^{*}	-0.10	-0.09	-0.04
	(0.42)	(0.32)	(0.34)	(0.10)	(0.09)	(0.07)
ipr^{Δ}_{t-2}			-0.13			0.17^{*}
			(0.23)			(0.10)
ipr^{Δ}_{t-3}			-0.04			0.12
			(0.20)			(0.17)
Daily Flows_{t-1}			0.35^{***}			
			(0.13)			
Total Net Assets_{t-1}			-0.00			
			(0.00)			
Daily Flows_{t-1}						0.12
						(0.09)
Total Net Assets_{t-1}						-0.00
						(0.00)
Constant	0.02	0.28	2.87	-0.01	0.23^{***}	0.22
	(0.05)	(0.20)	(2.30)	(0.01)	(0.05)	(2.08)
Observations	375	375	374	375	375	374
R^2	0.01	0.17	0.27	0.00	0.21	0.22
Fixed Effects	No	Month	Month	No	Month	Month

Table 5: Information Production Ratio and Money Fund Flows. Money Fund $\text{Flows}_t = \alpha + \beta ipr^{\Delta}_{t-1} + \gamma X_t + \varepsilon_t$ where "Money Fund Flows" are the total net asset flows as a share of the previous day's net asset value, calculated for either "prime institutional" or "prime retail" funds. X_t is a vector of controls including additional lags of ipr^{Δ}_{t-1}, flows from the fund, the level of net assets, and monthly fixed effects. The sample is daily and runs from January 2, 2008 to June 30, 2009. Robust standard errors reported in parentheses. Money fund flow data is from Schmidt et al. (2016); flow shares are multiplied by 100.

	Financials	Non-financials
Mean	0.95	1.59
Median	1.05	1.11
p-value	0.83	0.00
N	973	2,144

Table 6: Firm-Specific Volatility Identifying Assumption: Firm Beta Estimates. Table shows the mean and median beta estimates for financial and non-financial firms. The betas are estimated by regressing the firms' CDS spread on the financial market index separately for each year over the sample, which runs from 2006 to 2014. The summary statistics are averages across these year-by-firm beta estimates. The financial market index is an average of all financial firms' CDS spreads on that day. The p-value corresponds to a two-sided test where the null hypothesis is that the underlying beta average is equal to 1. N is the number of year-by-firm beta estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ipr_t	ipr_t	ipr_t	ipr_t	ipr_t^{Δ}	ipr_t^{Δ}	ipr_t^{Δ}	ipr_t^{Δ}
FINFIRM_t	0.24^{***}	0.21^{**}	0.16^{***}	0.94^{**}				
	(0.07)	(0.10)	(0.03)	(0.38)				
FINMKT_t		0.06	0.04^{*}	0.00				
		(0.05)	(0.02)	(0.06)				
$\Delta\text{FINFIRM}_t$					0.06^{***}	0.09^{***}	0.10^{***}	0.48^{***}
					(0.00)	(0.01)	(0.02)	(0.08)
ΔFINMKT_t						-0.02^{***}	-0.03^{**}	-0.05^{*}
						(0.01)	(0.01)	(0.02)
Constant	0.89^{***}	0.89^{***}	0.61^{***}	1.02^{***}	-0.01	-0.01	-0.06^{***}	-0.06^{***}
	(0.08)	(0.08)	(0.01)	(0.20)	(0.01)	(0.01)	(0.00)	(0.00)
Observations	468	468	468	468	467	467	467	467
R^2	0.28	0.29	0.95	0.93	0.14	0.14	0.44	0.42
Fixed Effects	No	No	Year-Month	Year-Month	No	No	Year-Month	Year-Month
Trimmed	No	No	No	Yes	No	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: ipr_t and Average Firm-Specific Volatility Estimates. Regression run on weekly data from 2006 through 2014. ipr_t is the information production ratio, and ipr_t^{Δ} are the AR(1) innovations to the ratio. FINMKT is aggregate volatility across all financials' CDS spreads and FINFIRM is the average firm-specific volatility, both calculated following Campbell et al. (2001)'s methodology. Dependent variables are standardized to have mean zero and unit variance. Columns (4) and (8) report estimates after winsorizing the independent variables at the 5 and 95 percent thresholds. Columns without fixed effects report standard errors in parentheses using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure. Columns with fixed effects report standard errors clustered by quarter.

Event	Date	Average Abnormal Information Production				
		Europe	**Core**	**Periphery**	**U.K.**	**U.S.**
2009 SCAP announcement	10-Feb-09	2.1	1.9	1.6*	6.5	−5.7**
2009 SCAP results	7-May-09	−0.8	−0.1	−2.1	−5.4*	−12.1*
2009 CEBS announcement	12-May-09	−2.1	−1.2	−2.0	−1.9	−3.9
2009 CEBS results	1-Oct-09	−0.9	−1.4	−1.1	0.1	4.9
2010 CEBS announcement	2-Dec-09	11.4	13.3	0.8	0.9	−0.5
2010 CEBS results	23-Jul-10	−2.3*	1.9*	−3.9**	−0.2	−5.2
2011 EBA announcement	13-Jan-11	0.3	4.8*	0.1	−1.3	0.9
2011 EBA results	15-Jul-11	−0.4	0.4	−2.8	0.9	0.7
2012 EU capital exercise announcement	8-Dec-11	−2.1*	9.8*	−3.7*	0.8	−3.5*
2012 EU capital exercise results	3-Oct-13	−1.2*	0.6	−1.3	0.8	1.2

Table 8: Information Production Event Study: Stress Tests. $ipr_t^\Delta = \alpha + \beta\mathbb{I}(\text{Event}_t) + \theta_t + \varepsilon_t$ where $\mathbb{I}(\text{Event})$ is an indicator variable equal to 1 if the date t is in the five days, including of the day itself, following the event, and 0 otherwise, and θ_t are year fixed-effects. The null hypothesis is that the event produces no incentive for markets to produce information on average over the following five days, so $ipr_t^\Delta = 0$. We run the test separately for each region: Europe, core Europe, periphery Europe, the U.K., and the U.S. Significance calculated using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Event	Date	Average Abnormal Information Production				
			Europe	**Core**	**Periphery**	**U.K.**	**U.S.**
Capital injection	U.S. capital injection	14-Oct-08	−13.6	−17.7*	−2.0	0.4	−4.3
	U.K. capital injection	8-Oct-08	−12.2	−10.6	−4.3*	−0.9	−5.6
Institution-Specific	Northern Rock	14-Sep-07	−0.8	−0.5	5.4	4.9	−1.3
	Dexia	11-Oct-11	−0.5	−13.5*	−1.0	0.9	−3.2**
	Lehman	15-Sep-08	3.3	5.9**	−0.3	2.7	1.0
	FSA + SEC bans shorting financials	19-Sep-08	5.6*	7.4*	2.4	19.1*	15.8*
	Fortis/TARP Fails	29-Sep-08	13.1	28.0	−2.2	−11.9**	−11.0
OMO/Asset Purchase	ECB begins buying Italian & Spanish bonds	8-Aug-11	−3.9	−14.6*	−1.1	1.7	0.9
	TALF/QE	25-Nov-08	−0.9	−3.8**	0.4	1.1	7.7
	"Whatever it takes"	26-Jul-12	−0.9	1.7	−1.1	0.2	−0.8
	August liquidity provision + BNP suspends subprime funds	9-Aug-07	−0.4	6.2	−2.3	4.3	12.6*
	Securities Market Program announced	10-May-10	0.3	−2.3*	−1.6	0.8	−0.2
	Outright Monetary Transactions announced	2-Aug-12	0.7	5.1*	2.0	−0.3	0.0
Periphery	Greece announces €300bn debt	10-Dec-09	−2.3*	1.8**	1.1	−4.0	−0.1
	Ireland €85bn deal	29-Nov-10	−1.9	5.4*	−4.2*	1.3*	−1.6
	Greece €110bn deal	3-May-10	−1.1	−3.3*	−4.3**	−3.8	−0.6
	Second Greece deal	22-Jul-11	−0.4	−0.2	−1.1	−1.1	−0.6
	Periphery concerns escalate	20-Sep-11	−0.4	−5.6*	1.1	−1.6**	−2.2
	Portugal €78bn deal	17-May-11	1.1	2.8*	−0.2	0.6	0.8

Table 9: Information Production Event Study: Other Event Types. $ipr_t^{\Delta} = \alpha + \beta\mathbb{I}(\text{Event}_t) + \theta_t + \varepsilon_t$ where $\mathbb{I}(\text{Event})$ is an indicator variable equal to 1 if the date t is in the five days, including of the day itself, following the event, and 0 otherwise, and θ_t are year fixed-effects. The null hypothesis is that the event produces no incentive for markets to produce information on average over the following five days, so $ipr_t^{\Delta} = 0$. We run the test separately for each region: Europe, core Europe, periphery Europe, the U.K., and the U.S. OMO is open-market operations. Significance calculated using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Average Abnormal Information Production					
	Europe	**Core**	**Periphery**	**U.K.**	**U.S.**	**All**
OMO/Asset Purchase	−0.6	−1.6	−0.2	1.3	3.2	0.7
Capital Injections	−9.5*	−9.8*	−3.7*	−0.9*	−4.5*	−4.7*
Institutional-Specific	4.3	5.5	0.9	2.8	0.6	2.4
Periphery	−0.6	1.2	−2.5	−0.8	−0.5	−0.6
US Stress Tests	−0.2	5.7	−2.0*	0.2	−1.6	0.6
EU Stress Tests	0.2	2.4	−1.7**	0.1	−0.8	0.0

Table 10: Average Abnormal Information Production by Event Type. $ipr_t^{\Delta} = \alpha + \beta \mathbb{I}(\text{Event}_t) + \theta_t + \varepsilon_t$ where $\mathbb{I}(\text{Event})$ is an indicator variable equal to 1 if the date t is in the five days, including of the day itself, following any of the events of a certain type, and 0 otherwise, and θ_t are year fixed-effects. The null hypothesis is that the event produces no incentive for markets to produce information on average over the following five days of the events, so $ipr_t^{\Delta} = 0$. We run the test separately for each region: Europe, core Europe, periphery Europe, the U.K., and the U.S. include events are those listed in Table 8 and Table 9. OMO is open-market operations. Significance calculated using robust standard errors clustered by quarter where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Annualized		Pre-Crisis		Global Financial Crisis		European Crisis	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Equities	S&P 350 Europe	26.5	11.1	−23.7	32.2	12.6	17.5
	Euro Stoxx 50	28.2	12.6	−22.6	34.5	9.2	22.9
	FTSE 100 (United Kingdom)	18.8	11.7	−23.9	35.4	12.5	16.5
	CAC 40 (France)	28.3	12.5	−23.7	35.0	10.6	22.7
	DAX (Germany)	53.3	12.7	−17.3	33.8	19.0	21.2
	IBEX 35 (Spain)	38.2	14.0	−15.4	33.9	5.0	26.2
	FTSE MIB (Italy)	21.0	11.4	−29.2	35.1	6.9	27.0
	PSI All-Share (Portugal)	57.8	8.6	−20.7	27.8	7.3	19.5
	ISEQ Overall (Ireland)	32.9	14.2	−42.8	41.6	17.3	20.7
	ASE General (Greece)	43.8	14.4	−29.2	34.3	−4.5	35.5
Real Estate	S&P Europe Property	31.4	14.4	−37.8	36.2	20.0	18.6
	S&P Europe REIT	n.a.	n.a.	−27.4	37.9	18.3	19.5
Sovereign Bonds	Germany	−1.4	2.5	7.6	5.1	5.1	4.7
	Greece	−0.5	2.4	5.6	5.3	7.6	31.2
	Ireland	−2.3	2.7	3.1	6.6	10.3	10.3
	Italy	−1.3	2.9	6.1	4.9	6.9	7.9
	Portugal	−0.8	2.4	7.0	4.9	8.6	15.3
	Spain	−1.7	2.6	6.8	5.0	6.3	8.2
Exchange Rates	EURUSD	9.3	5.7	3.0	13.0	0.1	9.9
	GBPUSD	7.5	6.4	−7.9	13.9	0.6	8.6
Fixed Income	iBoxx Euro Collateralized	−0.6	1.9	5.2	3.4	6.0	2.5
	iBoxx Euro Overall	−1.0	2.3	5.7	4.2	5.7	3.0
	iBoxx Corporate AAA	−3.0	2.0	−1.7	4.2	3.3	3.0
	iBoxx Corporate BBB	−0.3	1.6	3.6	5.1	6.3	3.6
CDS	iTraxx	4.8	0.3	2.3	3.9	2.2	2.9
Monoline Insurers	Syncora	51.2	25.9	−14.4	218.8	415.8	164.4
	MBIA	4.7	19.1	−30.2	144.8	61.3	67.6

Table 11: Reference Securities Summary Statistics. Table presents the summary statistics of the reference securities during three different periods: pre-crisis (January 2005 to June 2007), Global Financial Crisis (June 2007 to July 2009), and European debt crisis (July 2009 to April 2014). Numbers are annualized after taking moments from daily observations.

	(1)	(2)	(3)	(4)	(5)
ipr_{t-1}	1.61	−0.30	−0.30	−0.28	−0.47
	(1.01)	(0.27)	(0.27)	(0.24)	(0.30)
ipr^2_{t-1}		1.27***	1.26***	1.23***	1.41***
		(0.41)	(0.42)	(0.42)	(0.44)
$\mathbb{I}$(Periphery)			0.16	0.18	0.25
			(0.24)	(0.25)	(0.67)
Observations	98	98	98	98	98
R^2	0.32	0.68	0.68	0.69	0.73
Year Fixed-Effects	No	No	No	Yes	Yes
Country Fixed-Effects	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Information Production Ratio Predicts Subsequent Cost of Government Interventions in Financial Institutions. $\text{Cost/GDP}_{i,t} = \alpha + \beta_1 ipr_{i,t-1} + \beta_2 ipr^2_{i,t-1} + \varepsilon_{i,t}$ where i denotes the country and t is year. Independent variable is the centered and lagged information production rate for country i. $\text{Cost/GDP}_{i,t}$ is the net cost to the country i's government from that country's government interventions to support financial institutions as share of the country's 2008 nominal GDP. A negative net cost is net revenues. Cost data is from Eurostat, and only "to activities undertaken to support financial institutions. It does not include wider economic stimulus packages." $\mathbb{I}$(Periphery) is a dummy variable equal to 1 if the country is Greece, Ireland, Italy, Portugal, or Spain, and 0 otherwise. Robust standard errors reported in parentheses.

	(1) $\Delta\ln(\text{Funding})_t$	(2) $\Delta\ln(\text{Gross Loans})_t$	(3) $\Delta\ln(\text{Assets})_t$	(4) $\Delta\ln(\text{Total Equity})_t$
Information Production				
ipr_{t-1}	-1.22^{***}	-1.16^{***}	-1.32^{***}	-1.32^{***}
	(0.28)	(0.28)	(0.28)	(0.41)
Bank Characteristics				
$\ln(\text{Assets})_{t-1}$	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.12^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
$\text{Equity/Assets}_{t-1}$	-0.04	-0.49^{***}	-0.25^{**}	-1.17^{***}
	(0.13)	(0.14)	(0.12)	(0.15)
ROAE_{t-1}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
$\text{Provisions/PPOP}_{t-1}$	0.00	-0.00^{**}	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
$\text{Income/Assets}_{t-1}$	0.81	1.17^{**}	0.91^{**}	0.66
	(0.54)	(0.59)	(0.43)	(0.60)
Observations	2,543	2,506	2,551	2,533
R^2	0.24	0.21	0.25	0.15

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Information Production Ratio Predicts Bank Outcomes. We use Fitch bank balance sheet and clean it as follows: we limit to Euro countries, consolidated basis, semiannual reporting, exclude central banks, state and government banks, and supranational banks, IFRS reporting, and we keep only the 500 largest banks as based on their asset rank in the first half of 2007. We additionally require banks to have the following variables of interest: total assets, total equity, common equity, operating return on average assets, operating return on average equity, net income, pre-provision profits, provisions, gross loans. The dependent variables of interest are the log difference in total funding, gross loans, total assets, and total equity. The independent variables (all lagged by 1 period, 6 months since the data is semiannual) are *ipr*, total assets, total equity to assets, return on average equity, provisions to pre-provision profit, and income to assets. We winsorize all variables at the 5 and 95 percent level to reduce the influence of outliers. We also include country and bank fixed-effects and multiply the variables by 100. Robust standard errors reported in parentheses.