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IMF Working Paper

Investor Information and Bank Instability During the European Debt Crisis

Silvia Iorgova and Chase P. Ross

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IMF Working Paper

Monetary and Capital Market Department

Investor Information and Bank Instability during the European Debt CrisisPrepared by **Silvia Iorgova and Chase P. Ross**¹

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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 true during crises. We measure daily information production using data from credit default swap spreads during the global financial crisis and the subsequent European debt crisis. We study abnormal information production around major events and interventions during these crises and find that, on average, capital injections reduced abnormal information production while early European stress tests increased it. We also link information production to outcomes: high levels of information production predict bank balance sheet contraction and higher government expenditures to support financial institutions. In an addendum, we show information production on nonfinancials dramatically increased relative to financials at the height of the COVID-19 crisis, reflecting the nonfinancial nature of the initial shock.

JEL Classification Numbers: G01, G20, G21, G28

Keywords: information production, financial crises, safe asset

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I. INTRODUCTION

Financial crises are information events. In the absence of market disruptions, the prices of short-term debt securities—particularly of debt that can serve as a medium of exchange—are relatively stable. Such debt is considered information *insensitive* and acts as a safe asset. When market uncertainty rises, investors’ desire to acquire an advantage by producing private information destabilizes the value of some short-term debt and makes it information *sensitive*. The result is the creation of private information (“information production”) on banks’ balance sheets that leads to higher risk for bank runs. Information production dynamics before crises can reveal growing instabilities, while information production dynamics during crises depend, in part, on the adequacy and credibility of policymakers’ actions. In this paper, we measure daily information production in Europe in the context of the global financial crisis and the subsequent European sovereign debt crisis, show the effects of different policies on information production, and link information production to the ultimate taxpayer cost of the crisis.² We argue that policymakers’ information management efforts are first-order important during financial crises.

The information insensitivity provided by safe assets is a necessary component of any financial system, acting as the “lubricant” of trust in financial transactions.³ Safe assets are money-like because they are liquid and provide a store of value. They aid capital preservation in portfolio construction and are a key source of liquid, stable collateral in repurchase (repo) agreements and derivatives markets. 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 that provide safe assets for investors take many forms, including bank deposits, commercial paper, and repurchase agreements. Dang et al. (2017) argue that policymakers want banks’ debt to be information insensitive, so there is little incentive for investors to produce private information on such debt, thereby eliminating adverse selection risk for uninformed agents. Financial crises occur when the demarcation between safe and risky assets blurs.

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 not equipped to perform detailed credit analysis of ABS collateral and did have an incentive to do so.⁴ In most states of the world, credit research on safe assets is unprofitable because the collateral is far from bankruptcy. That creditors accept collateral backing money no questions asked is an essential

² 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.

³ For a more detailed discussion on safe assets and global financial crisis, see Iorgova et al. (2012).

⁴ This paper only covers wholesale creditors and not retail creditors.

feature of safe assets. But, as creditors during the crisis 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.

An important finding in the literature is that the onset of crises is associated with price and nonprice effects from the rise in the information sensitivity of debt. Such changes in information sensitivity can occur via nonprice adjustments (e.g., less debt issuance or higher repo haircuts)—as shown by Dang, Gorton, and Holmström (2019). The observed drops in liquidity act as a mitigant against increases in asymmetric information and adverse selection problems. Research also finds close links between information sensitivity and price effects. For example, Benmelech and Bergman (2017) find that during the 1873 and 2008 financial crises, bond values fell in tandem with the decline in bond liquidity, consistent with an adverse selection model—precisely the types of friction that safe assets are meant to avert. Gorton (2008) highlights the channels through which information production ignited the global financial crisis.

The rise in the inefficiency of information production—including information asymmetries—during crises underscores the importance of well-targeted policy responses. Such policies can be varied in nature and shape the information environment. Some address information production explicitly (e.g., short-sale bans or stress tests). Others manage information implicitly (e.g., asset purchase programs). 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 investors’ incentive to produce private information by making the banking system’s exposures and sensitivities common knowledge.

We study empirically information production in crisis episodes, including during the European debt crisis. Our contributions to the literature are threefold. First, we create a novel measure of information production—the “information-production ratio” ($i\text{pr}_t$)—and link it to real outcomes. The $i\text{pr}_t$ is constructed as the cross-sectional standard deviation of credit default swap (CDS) spreads of financial companies relative to nonfinancial companies. A considerably faster growth of information production in the financial sector than in the nonfinancial sector elevates the risks of bank runs and safe asset destruction.⁵ Second, we measure *abnormal* information production in response to various policy responses, including stress tests and public interventions, as well as important country-specific events. 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, Igan, and Pinheiro 2020; and Sahin, Haan, and Neretina 2020). Third, 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

⁵ The $i\text{pr}_t$ measure is not a restatement of a average CDS spreads—the two are uncorrelated.

regression to select a set of reference securities that explain most of the variation in banks' CDS returns. Finally, we link $i\text{pr}_t$ to real outcomes and bank balance sheet dynamics.

Our work is also 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, Gorton, and Holmström 2015, 2019; and Dang et al. 2017). Our paper is most closely related to Chousakos, Gorton, and Ordoñez (2020), who measure information production empirically via the cross-sectional standard deviation of equity returns.

Our results show that relative information production for the banking sector spiked 22 times after the Lehman Brothers' bankruptcy in 2008, fell in the intervening years, and surged again during the European debt crisis. Importantly, the 2010 and 2012 European stress tests were associated with a large reduction in information production in periphery countries—a finding which did not hold at the aggregate Europe-wide level. We find the 2009 U.S. stress tests to be linked to a substantial decline in abnormal information production. Capital injections and the interventions in European periphery countries reduced abnormal information production, but other intervention types did not have a statistically significant effect.

The reference securities analysis shows that banks' returns covaried strongly with traded securities during both the global financial crisis and the European debt crisis. Yet the model selects economically different reference securities for the two crises. During the global financial crisis, the selected reference securities include the iTraxx 5y, iBoxx BBB Europe, Greek government bonds, and German Bunds. During the European debt crisis, the model changes to include Irish and Spanish sovereign bonds, and periphery equity indices, reflecting the shift of stress toward these countries' government debt and commercial property.

We test the accuracy of the reference security model with respect to changes in the information production measure ($i\text{pr}_t^A$). 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, $i\text{pr}_t^A$'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.

Importantly, higher levels of information production in preceding periods predict the subsequent cost to the government of direct intervention in financial institutions at the year-country level. The effect is exponential: a unit higher level of the polynomial $i\text{pr}_{t-1}^2$ within a country predicts a 1.3 percentage point increase in financial intervention costs the following year as a share of that country's GDP. For European banks, we also find that a one-unit higher level of information production in the preceding year is associated with a contraction of bank lending (0.8 percent), total assets (1.1 percent), and total equity (0.9 percent) in the subsequent year.

Finally, the outbreak of COVID-19 in March 2020 led to a dramatic increase in the cross-sectional variance across nonfinancial companies, which remains elevated. Unlike the 2008

financial crisis, the trigger of the COVID crisis originated outside the banking system, and $i\text{pr}_t$ fell in the United States and Europe. As of August 2020, the cross-sectional standard deviation of nonfinancial companies is roughly 10 times its level at the beginning of the year, whereas financials are only 13 percent higher.

The rest of the paper is organized as follows. Section II briefly discusses the theory underpinning information production. Section III describes our methodology and data, including the information production measurement process. Section IV presents our empirical results. Section V concludes.

II. A THEORETICAL 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, Gorton, and Holmström (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, Liang, and Suarez 2012), repos in 2008 (Gorton and Metrick 2012), and collateralized-loan obligations during the COVID-19 shock (Foley-Fisher, Gorton, and Verani 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.^{6,7} Deposit insurance did not change banks' opacity: Badertscher, Burks, and Easton (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:

$$\Psi = k - e + \omega - \frac{\gamma}{d} \quad (1)$$

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 investment in worthy projects.⁸ 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 $\Psi \leq 0$.

⁶ 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.

⁷ 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 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."

⁸ See Dang et al. (2017), equation 7.

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 $w \in [0,1]$:

$$d = wd^a + (1 - w)d^r \quad (2)$$

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, Metrick, and Ross (2020) argue that many investors inferred banks' solvency using subprime mortgage price indices during the global financial crisis.

Combining the previous equations yields:

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

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 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, Malz, and Pozsar (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.

III. METHODOLOGY AND DATA

A. 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 nonfinancial companies. We term this new measure the “information-production ratio” ($i\text{pr}_t$). 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. (2015) 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 language of the theoretical set-up above, the probability of a bad state d and the incentive to acquire private information Ψ are low. The face value of secured, 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 nongovernment entities with modified-modified restructuring (MM and MM14) clauses. All data is sourced from Markit and Bloomberg. The sample of CDS contracts includes roughly 3.4 million day-firm observations, of which 1.2 million are financial companies. We do not use CDS contracts for senior secured debt because the data are sparse: only 25,000 observations for financials, with only 13 data points available before 2007. 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. We use analogous data for the U.S. sample, except that these are dollar-denominated contracts with modified-restructuring clauses (MR and MR14). CDS markets are more mature in the United States, so we also require that the contract has a Markit rating. Nonrated contracts constitute a much larger share of the data in the United States relative to European countries, and the spreads are not available consistently from day to day. We drop a handful of companies with outlier spreads. In addition to the CDS data, we use price and return data collected from Bloomberg and bank-specific balance sheet information from Fitch.

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

$$\sigma_{t,Financials} = \sqrt{\frac{1}{n} \sum_i (CDS_{i,t} - \bar{\mu}_{i,t})^2} \quad (4)$$

where $CDS_{i,t}$ is the CDS spread for financial company i , n is the number of financial companies in the sample, and $\bar{\mu}_{i,t}$ is the average CDS spread across all financial companies, all on day t . An equivalent measure for nonfinancial companies is $\sigma_{t,Non-financials}$. We define the *information-production ratio*, $i\text{pr}_t$ as the cross-sectional standard deviation within financial companies divided by the identical measure for nonfinancial companies:

$$i\text{pr}_t = \frac{\sigma_{t,Financials}}{\sigma_{t,Non-financials}} \quad (5)$$

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, $i\text{pr}_t^\Delta$. Specifically, we assume that Ψ_t is affine in $i\text{pr}_t$:

$$\Psi_t = a + b (i\text{pr}_t) \quad (6)$$

Following He, Kelly, and Manela (2017), we estimate innovations to $i\text{pr}_t$ based on the residual from an AR(1) process estimated from daily data from 2006 through 2014: $i\text{pr}_t = \rho_0 + \rho i\text{pr}_{t-1} + u_t$. We convert the innovations to a growth rate as:

$$i\text{pr}_t^\Delta = \frac{u_t}{i\text{pr}_{t-1}} \quad (7)$$

Our $i\text{pr}_t$ measure controls for information production relative to the nonfinancial 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 nonfinancial sector, the risks of bank-runs and safe asset destruction are high. Information production rose across the board throughout 2008 as the crisis unfolded and economies slowed down. Yet information production in the financial sector ($\sigma_{t,Financials}$) grew 22 times its 2006 average immediately after Lehman to settle around 7 times at end-2008, but only doubled in the nonfinancial sector, as shown in Figure 3.

Three important properties of the $i\text{pr}_t$ measure are worth noting. First, as a measure of the relative dispersion of the CDS spreads of financial and nonfinancial companies, the $i\text{pr}_t$ 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) and Krishnamurthy and Muir (2015) who find 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 $i\text{pr}_t^A$: except for the United Kingdom, 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 $i\text{pr}_t$ is a novel measure and not a restatement of average CDS spreads, the market return, or other common cyclical measures, as shown in Figure 4. Regressing $i\text{pr}_t$ on CDS spreads shows no statistically significant relationship. We also show that $i\text{pr}_t^A$ is not explained by other common market stress measures, as shown in Table 4. We find no statistically significant relationship between $i\text{pr}_t^A$ 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 $i\text{pr}_t^A$ and the S&P 350 Europe, the FTSE100, the S&P 500, or bank equity indices for Europe, the United Kingdom, and the United States at the 5-percent level, and only the European bank index is correlated at the 10-percent level.

B. Abnormal Information Production and Policy Responses

We conduct event studies to measure abnormal information production. These studies examine which policies or interventions were effective in reducing information production. To this end, we test whether $i\text{pr}_t^A$, the $i\text{pr}_t$ innovations estimated via the AR(1) process, are statistically different from zero in the five trading days after an event since $\mathbb{E}[i\text{pr}_t^A] = 0$ by construction. 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.

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. Specifically, we test information production by comparing the average $i\text{pr}_t^A$ in the five days after the event, including the day itself, relative to the average $i\text{pr}_t^A$ on all other days in the sample using:

$$i\text{pr}_t^A = \alpha + \beta \mathbb{I}(\text{Event}_t) + \theta_t + \varepsilon_t \quad (8)$$

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.

C. 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 explain most of the variation in banks’ CDS returns. The optimal reference securities are identified from a set of candidate securities using a LASSO (shrinkage) regression. The regression is meant to determine 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:

$$\Delta d_t^r = \gamma_0 + \gamma_1 r_t^{CDS} \quad (9)$$

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

$$r_t^{CDS} = \alpha + \beta_1 r_{1,t}^{ref} + \beta_2 r_{2,t}^{ref} \dots + \beta_N r_{N,t}^{ref} + \varepsilon_t \quad (10)$$

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 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 the least absolute shrinkage and selection operation (LASSO) to find the best descriptors of a panel of bank CDS returns. We identify the optimal model using the extended Bayesian information criterion. 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

$$r_{i,t}^{CDS} = -1 \times \left(\frac{CDS_{i,t-1}}{250} + \Delta CDS_{i,t} \times RVPV01_{t-1} \right) \quad (11)$$

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;
- *Sovereign Bonds*: Bloomberg-Barclays All Bonds Total Return indices for Portugal, Ireland, Italy, Greece, Spain, and Germany;
- *Exchange Rates*: EURUSD, GBPUSD;
- *Fixed Income*: iBoxx Euro Collateral 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 difference.

We also test the accuracy of the reference security model with respect to ipr_t^A . 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, $r_{i,t}^{CDS}$ and obtain the predicted returns, $\hat{r}_{i,t}^{CDS}$. We then calculate the average model residuals by averaging across all company-specific residuals on a given day t :

$$\bar{\varepsilon}_t = \frac{1}{N} \sum_{i=1}^N (r_{i,t}^{CDS} - \hat{r}_{i,t}^{CDS}) \quad (12)$$

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 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:

$$\begin{bmatrix} ipr_t^A \\ \bar{\varepsilon}_t \end{bmatrix} = \mathbf{a}_0 + \mathbf{A}_1 \begin{bmatrix} ipr_{t-1}^A \\ \bar{\varepsilon}_{t-1} \end{bmatrix} + \dots + \mathbf{A}_{t-k} \begin{bmatrix} ipr_{t-k}^A \\ \bar{\varepsilon}_{t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \quad (13)$$

where \mathbf{a}_0 is a vector of intercept terms and $\mathbf{A}_1, \dots, \mathbf{A}_{t-k}$ are 2×2 matrices of coefficients of on lags of ipr_t^A and $\bar{\varepsilon}_t$. We select 15 trading-day lags, k , using Akaike's information criterion.

D. Information Production, Bank Outcomes, and Real Outcomes

In the final piece of our empirical work, we relate $i\text{pr}_t$ to outcomes in terms of the cost of financial institution interventions to governments and banks' balance sheet dynamics.

We regress country-specific lagged $i\text{pr}_{t-1}$ on the net cost of government interventions to support financial institutions, as calculated by Eurostat:

$$\text{Cost/GDP}_{i,t} = \alpha + \beta_1 i\text{pr}_{i,t-1} + \beta_2 i\text{pr}_{i,t-1}^2 + \varepsilon_{i,t} \quad (14)$$

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. $\mathbb{I}(\text{Periphery})$ is a dummy variable equal to 1 if the country is Greece, Ireland, Italy, Portugal, or Spain, and 0 otherwise.

To make the linear term coefficient easier to interpret we center $i\text{pr}_{t-1}$ to represent the rate of change in cost-to-GDP when $i\text{pr}_{t-1}$ is equal to its mean (if we do not demean, the linear term would reflect the rate of change when $i\text{pr}_{t-1} = 0$, which is outside the empirical range of $i\text{pr}_{t-1}$). The sample includes 14 countries, each with eight years of observations.⁹

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 excluding 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 $i\text{pr}$, 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 percent 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.

⁹ We are limited to countries with a sufficiently rich cross-section of CDS spreads for financial and nonfinancials because we use country-specific $i\text{pr}_{t-1}$ rather than region-specific. The 14 included countries are: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

IV. RESULTS

First, we outline the evolution of information production in the context of the global financial crisis and the European debt crisis. Second, we discuss the key findings of the event study on the link between abnormal information production and policy responses. Third, we test the reference security view of financial crises. Fourth, we relate ipr_t to bank and real outcomes. At the bank level, we show that ipr_t predicts bank balance sheet contraction; at the country level, we show high levels of ipr_t predict higher subsequent government costs of financial interventions. Finally, we show that ipr_t fell through the worse phases of the COVID-19 crisis, reflecting the fundamentally different nature of the recent shock.

A. Evolution of Information Production

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 (green line in Figure 1). It then 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.

Figure 1 plots ipr_t and ipr_t^{Δ} . We can slice the data to make more granular ipr_t measures, although smaller slices are subject to larger measurement error. Figure 2 shows the ipr_t for Europe—also including the United Kingdom, periphery Europe and core Europe—and the United States.

In Figure 2, 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, as expected. In the core, ipr_t spiked dramatically in October 2008 but remains low at all times, except 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.

B. Abnormal Information Production

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 Europe (both in its core and periphery) but not in the United Kingdom and the United States.

Table 5 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 (−5.7 percent) and results (−12.1 percent). An average daily $i\text{pr}_t^A$ 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 $i\text{pr}_t^A$ fell in the United States following the 2012 test only.

The heterogeneity in information production across member states 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.¹⁰ 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: 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. While the tests for the German banks may have done little to allay investors’ fears (especially given the haircuts on Greek sovereign debt are no larger than the actual decline in GGB prices since Dec-09), the market has not to date questioned the German state’s ability to support its banking system. By contrast, much of the sell-off in Bonos in May and June was due to the market’s concerns that the Spanish government ... would not be able to raise funds

¹⁰ 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.

to refinance its banks. ...**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. [emphasis added]

Table 6 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 take the results with a grain of salt given 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 United States, 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 intervention type is the most effective by scanning the rows of Tables 5 or 6. 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 7. The test is identical to previous tests, except rather than isolating a single event we instead set $I(\text{Event}) = 1$ 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 Europe (-9.5 percent) and smaller, but still significant, in the United Kingdom (-0.9 percent). While not significant for 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.

C. Reference Securities

The LASSO results yield two insights. First, banks’ returns covaried strongly with traded securities during both the global financial crisis and the European debt crisis. Table 6 shows the model-selected basket’s R^2 nearly quadrupled from pre-crisis to the GFC (1.1 percent to 3.9 percent) and grew eight-fold during the European debt crisis (from 1.1 percent to 8.0 percent). The R^2 coefficients match our intuition: pre-crisis, bank CDS returns should not covary strongly with any indicator because senior bank debt was information-insensitive. With the onset of the crises, senior bank debt began to covary more closely with traded securities as bank debt became more information-sensitive. Baskets of reference securities therefore turned into better proxies of banks’ soundness, including solvency.

Second, the model selects economically different reference securities when estimated separately for the global financial crisis and the later European debt crisis. Figure 5 plots the betas of the model-select optimal portfolio of reference securities. During the global financial crisis, the model selects the early stages of stress in the periphery—Greece—and indicators of the real economy’s performance in corporate bonds. The reference securities in the European debt crisis shift toward the periphery and toward property returns.

Pre-crisis, only one variable, the iTraxx, had a large beta (0.16). Because we examine the cross-section of bank CDS returns, the iTraxx index is the CDS equivalent of a market factor, and for the pre-crisis period, the LASSO effectively selects the CDS market equivalent of the capital asset pricing model (CAPM). The selected reference securities in the global financial crisis period still include the iTraxx (0.52, roughly triple its pre-crisis beta), iBoxx BBB (0.28), Greek sovereign bonds (0.09), iBoxx AAA (0.08), and German bunds (-0.36). 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, the model drops the Greek sovereign bonds and adds Spanish and Irish sovereign bonds (0.04 and 0.03, respectively). The iBoxx’s beta shifts from 0.08 to -0.19 , and the Bund beta attenuates to -0.07 . The model for the European debt crisis also selects periphery equity indices (PSI, IBEX, ISEQ, and the ASE) and the S&P Europe Property index, although they all have smaller betas.

We also test the accuracy of the reference security model with respect to $i\text{pr}_t^A$. Figure 6 plots the cumulative orthogonalized impulse response functions. The left panel shows the effect of an impulse on the model residual on $i\text{pr}_t^A$, the middle panel shows the effect of an $i\text{pr}_t^A$ 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, $i\text{pr}_t^A$ ’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.

D. Information Production and Outcomes

In the final piece of our empirical work, we relate $i\text{pr}_t$ to real outcomes: outcomes in terms of the cost of financial institution interventions to governments and banks’ balance sheet dynamics.

One important finding is that the level of information production in a country predicts the government’s subsequent cost of interventions in financial institutions (Table 7).¹¹

Column one of Table 7 shows a positive correlation between the centered $i\text{pr}_{t-1}$, although the effect is not significantly different from zero. Including a squared centered term, $i\text{pr}_{t-1}^2$, 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 $i\text{pr}_{t-1}$ is 0.95, so an $i\text{pr}_{t-1}$ one standard deviation above average predicts a cost of financial intervention in the next year of 0.68 percent of GDP.

Table 8 shows the result from regressing Europe-wide $i\text{pr}_{t-1}$ and bank balance sheet variables. It shows when $i\text{pr}_{t-1}$ is one unit higher, roughly equal to one standard deviation, funding falls the next semiannual period by 1.0 percent, gross loans by 0.8 percent, total assets by 1.1 percent, and total equity by 0.9 percent. The coefficients show that a higher $i\text{pr}_{t-1}$ implies banks, on average, delever as assets fall faster than equity. However, the $i\text{pr}_{t-1}$ 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.

¹¹ Figure 7 gives a scatterplot of the two variables.

E. Impact of COVID-19

We calculate $i\text{pr}_t$ 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 2020.¹² Figure 8 shows the fundamental fact that COVID-19 did not begin as a financial crisis. In March 2020, the cross-sectional variance across nonfinancial 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 $i\text{pr}_t$ fell in the United States and Europe (including the United Kingdom). As of August 2020, the cross-sectional standard deviation of nonfinancial companies is roughly 10 times its level at the beginning of the year, whereas financials are only 13 percent higher.

V. 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 nonfinancial 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 solvency probabilities. We find that reference securities during pre-crisis, the global financial crisis, and the European debt crisis are economically and statistically unique from one another. 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 $i\text{pr}_t$ forecasts higher costs to the government of financial interventions and bank balance sheet contraction. After the outbreak of COVID-19, we show that the $i\text{pr}_t$ fell considerably, reflecting the fundamentally nonfinancial nature of the shock.

¹² We also exclude Norske Skogindustrier ASA from our European sample as its data is unrealistically volatile.

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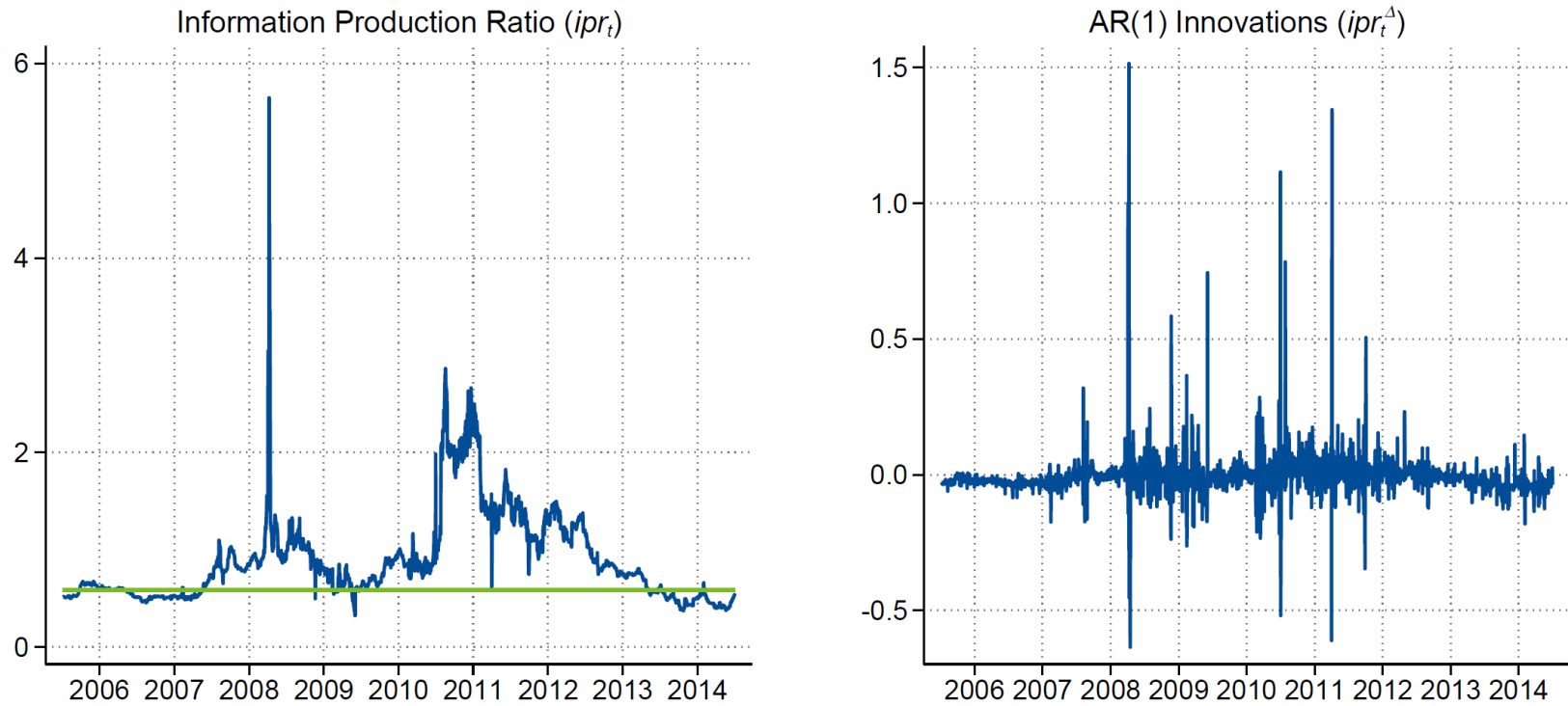
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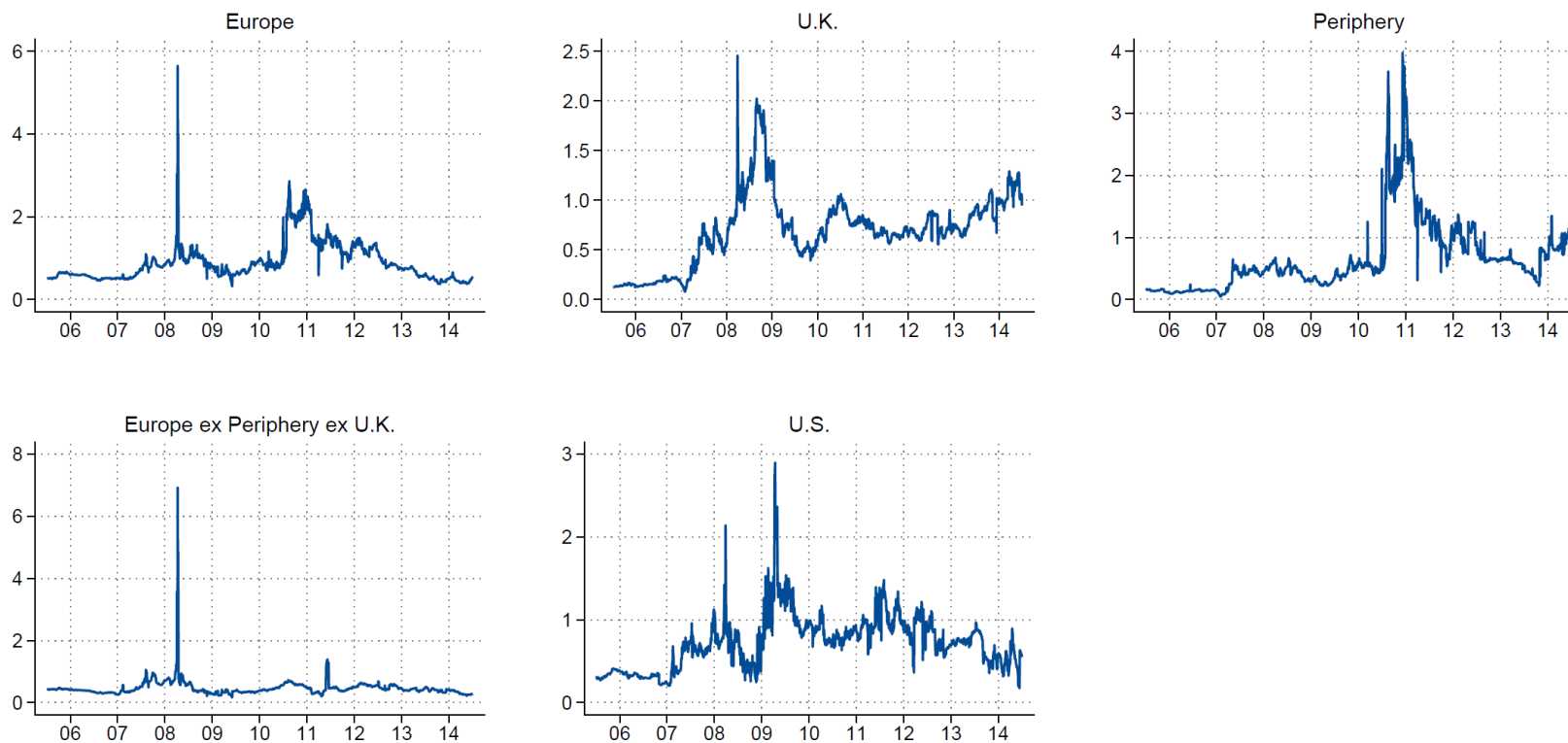
VI. FIGURES

Figure 1. Information Production Ratio in the Europe: Level (ipr_t) and Innovations (ipr_t^Δ)



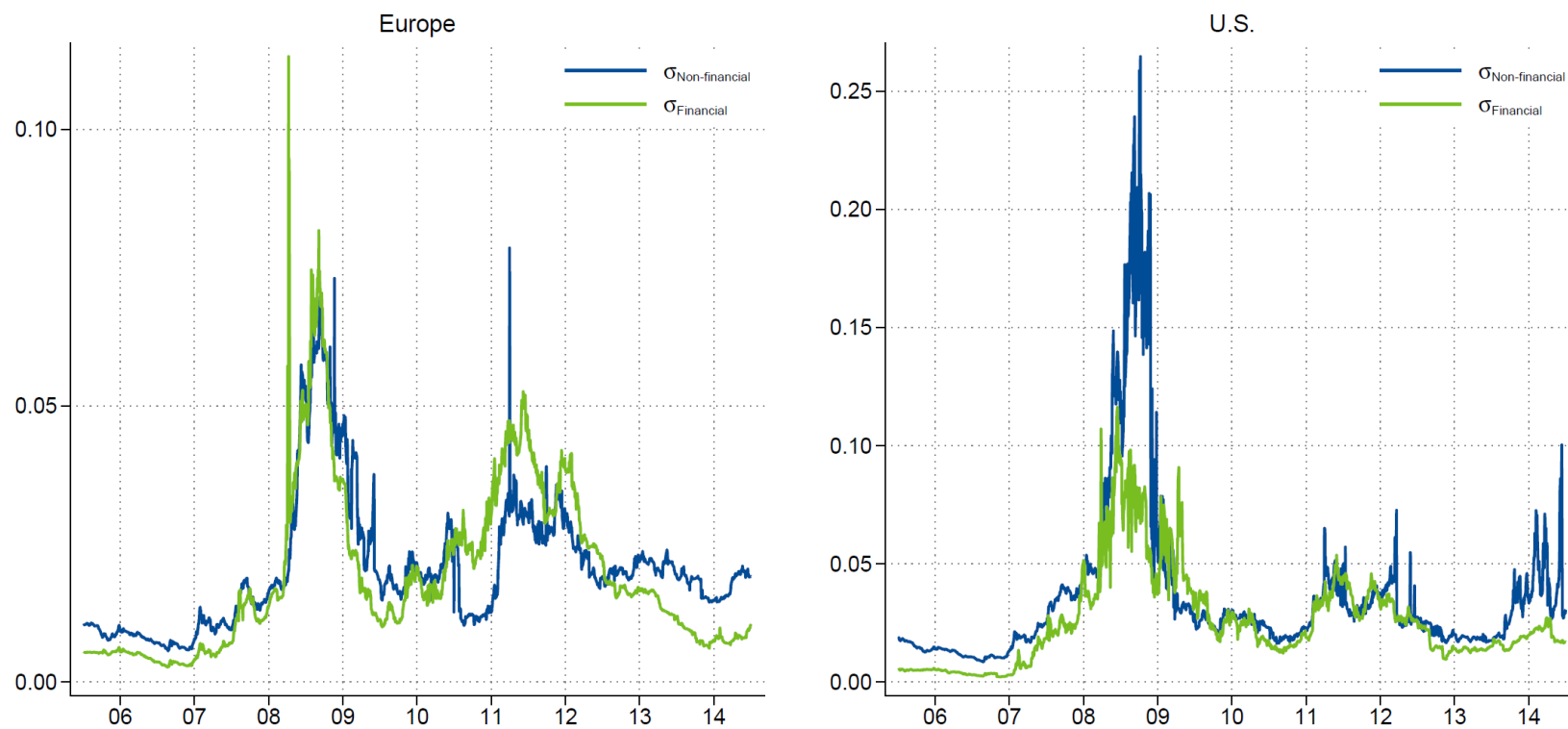
¹ We plot the “information-production ratio,” ipr_t , on the left and the innovations to ipr_t , ipr_t^Δ , on the right. The green line on the left panel is the average level of ipr_t in 2006, pre-crisis. ipr_t is the daily cross-sectional standard deviation of five-year euro-denominated senior secured debt CDS spreads within financial companies divided by the same measure within nonfinancials, excluding government reference entities.

Figure 2. Information Production Ratio Across Countries¹



¹ We plot the “information-production ratio,” ipr_t , by country using the same methodology as the aggregate Europe-wide ipr_t ; the United States measure a few different cleaning steps, which are described in section III. ipr_t is the daily cross-sectional standard deviation of five-year euro-denominated senior secured debt CDS spreads within financial companies divided by the same measure within nonfinancials, excluding government reference entities, within a region.

Figure 3. Evolution of $\sigma_{Financial}$ and $\sigma_{Non-financial}$ ¹



¹ Plot compares the cross-sectional standard deviation of CDS spreads in Europe and the United States.

Figure 4. Europe-wide Information Production Ratio and Average Financials' CDS Spread

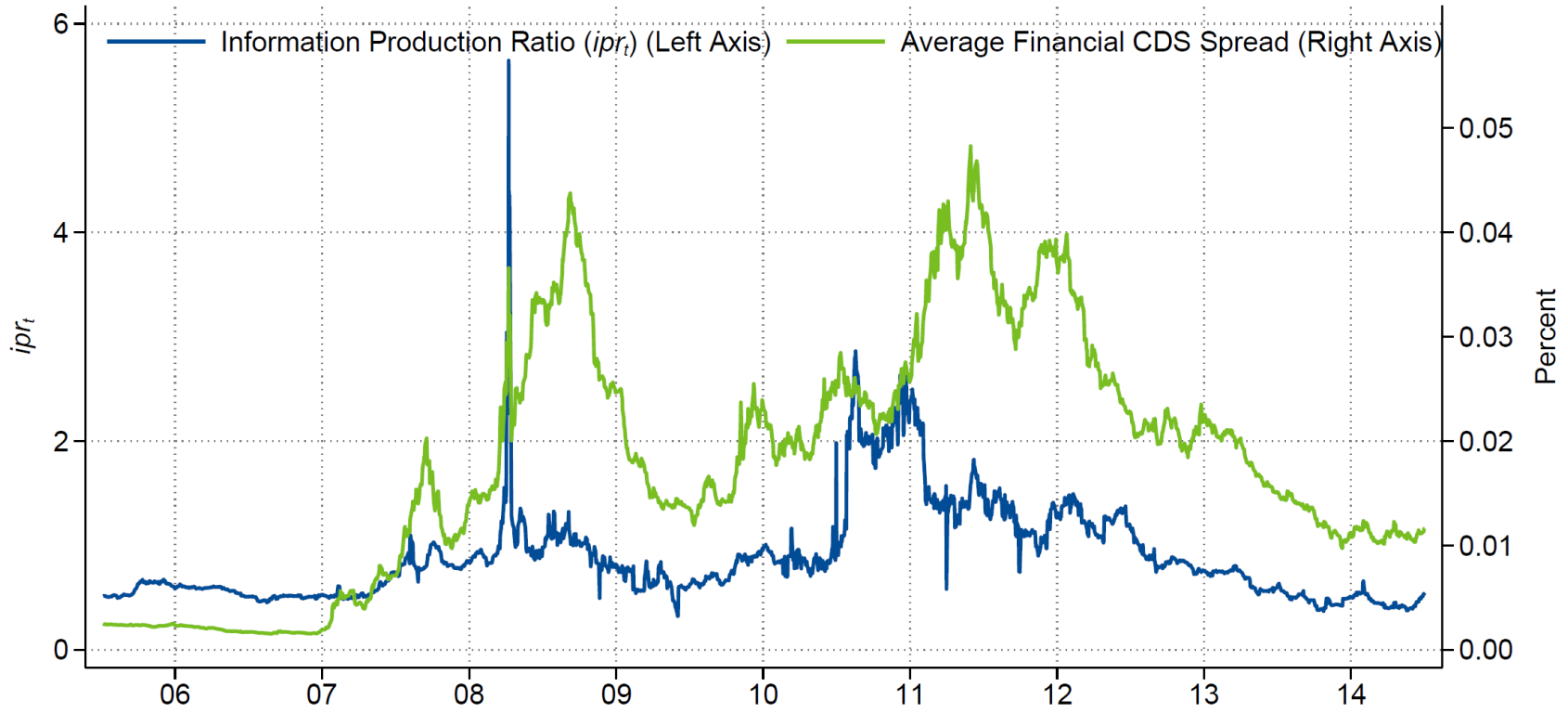
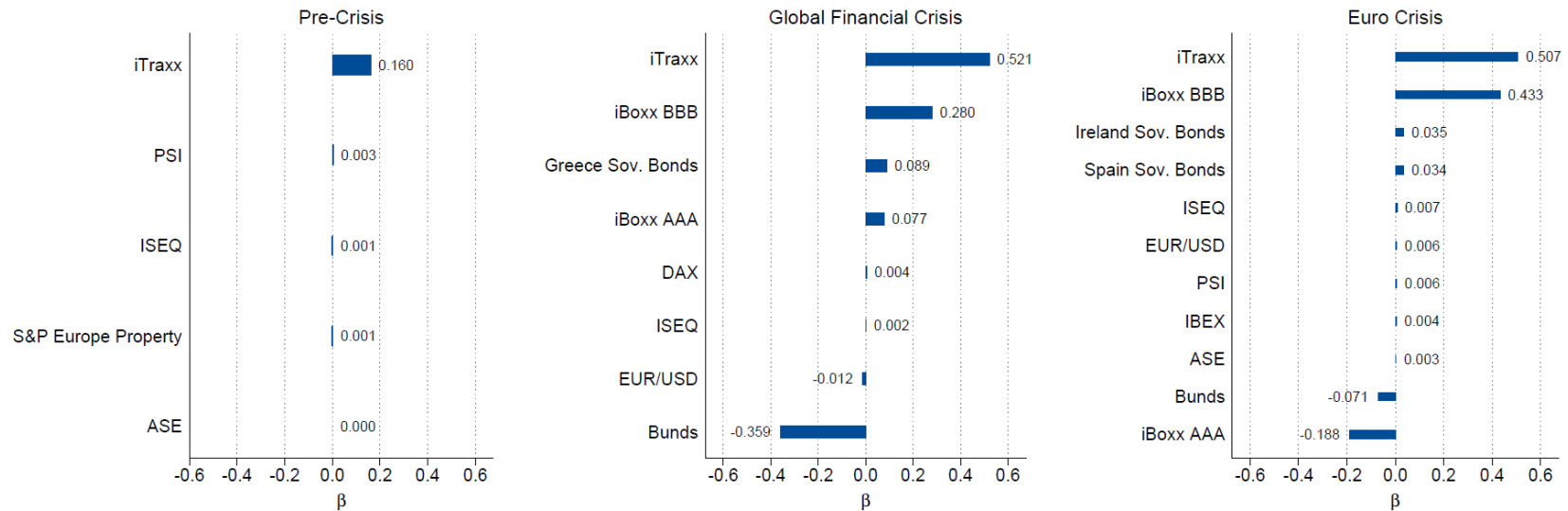
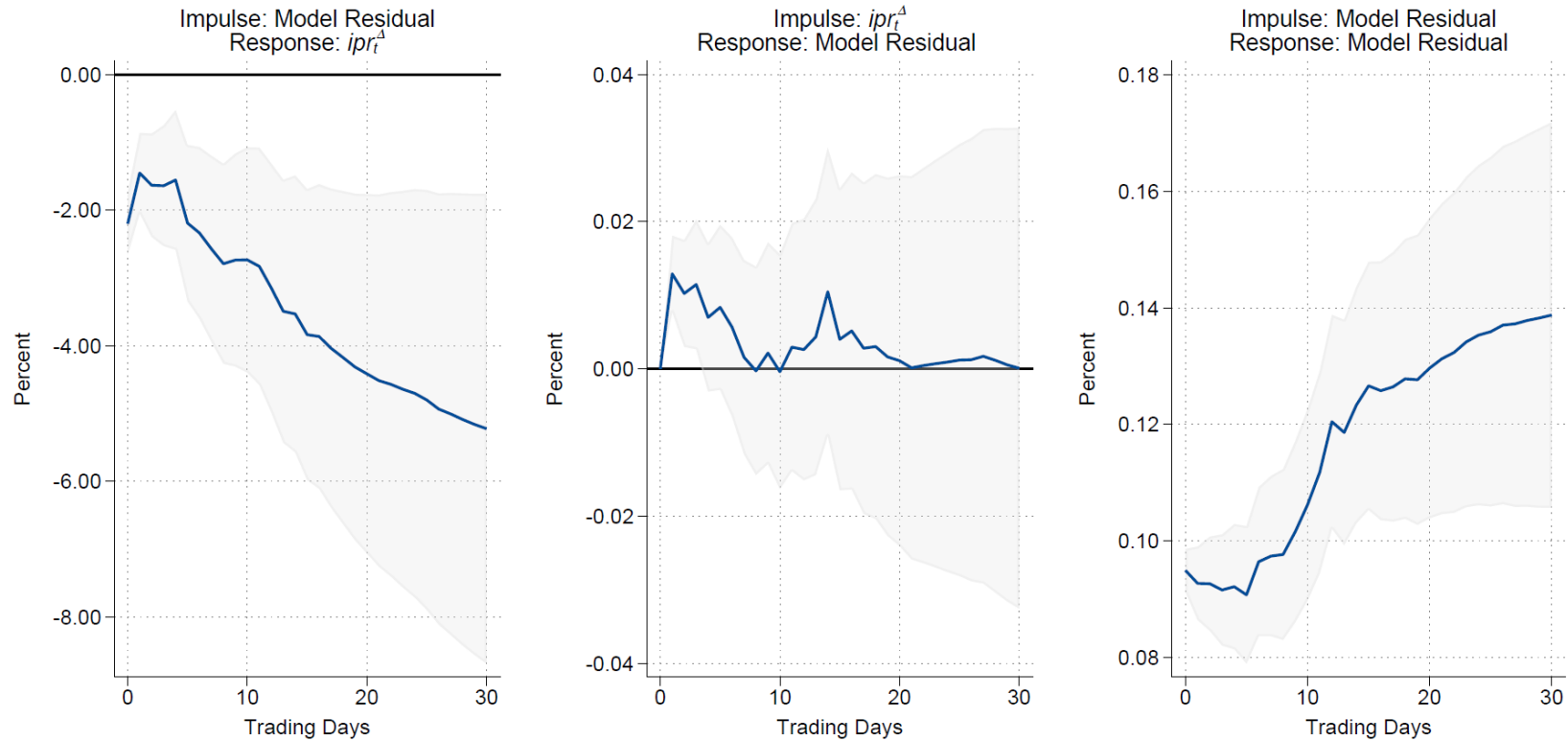


Figure 5. Reference Securities' Betas¹



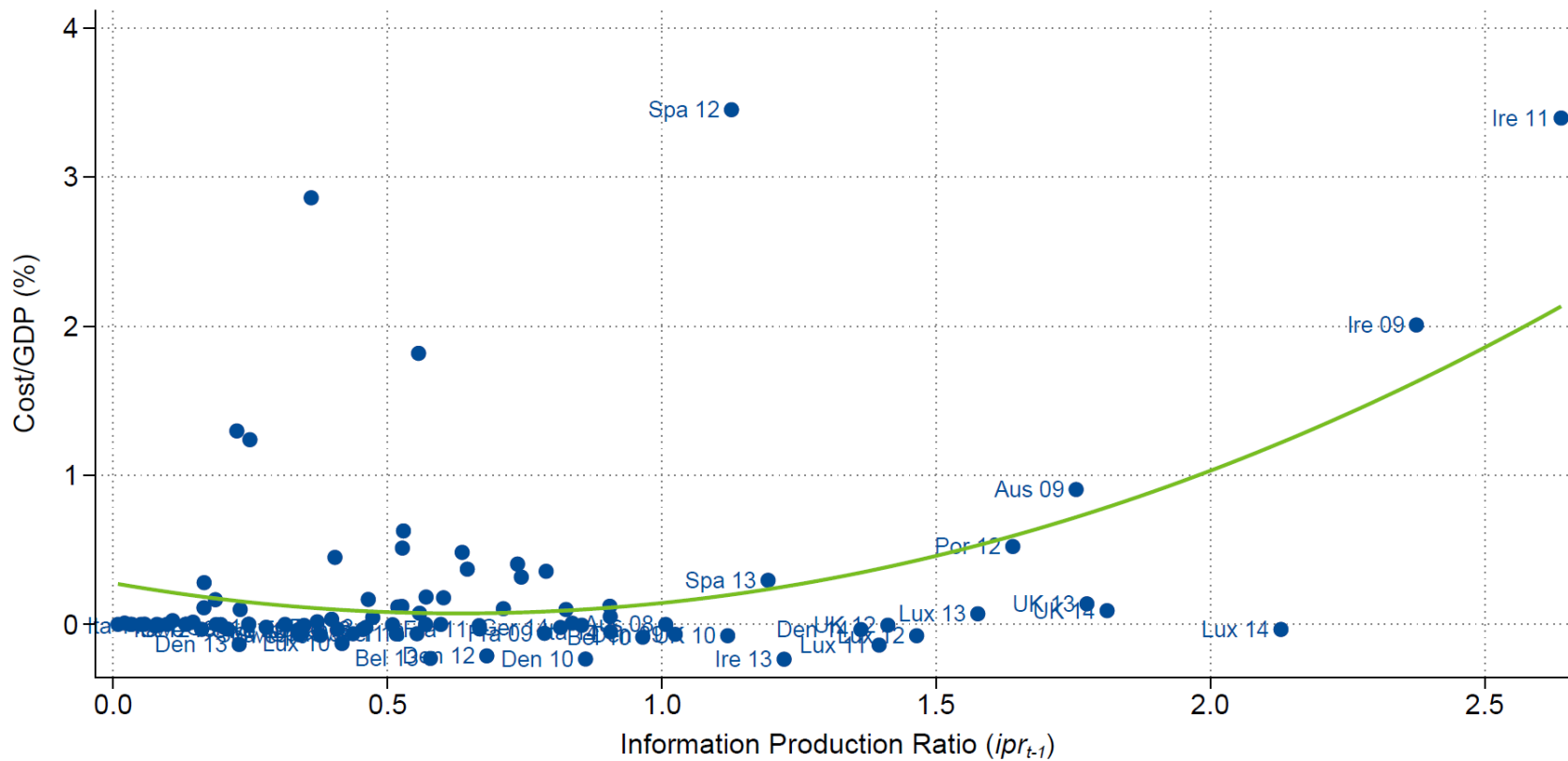
¹ Plot gives the betas of the LASSO-selected reference securities which best explain the cross-section of European bank CDS returns over the pre-crisis (before June 1, 2007), global financial crisis (June 1, 2007 to July 1, 2009) and European debt crisis (August 4, 2009 to April 10, 2014). If a reference security is not selected for a specific sample, there is no bar. 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 five-year index, a portfolio of liquid CDS contracts.

Figure 6. Vector Autoregression Impulse Responses¹



¹ Plots show cumulative orthogonalized impulse response functions after the estimation of the two-variable vector autoregression model described in equation 13, using the model residuals and innovations to the Europe-wide ipr_t over the crisis sample (June 2007 to April 2014). 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 debt crisis.

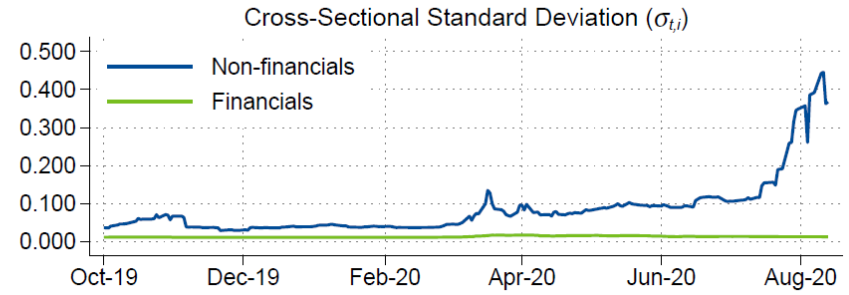
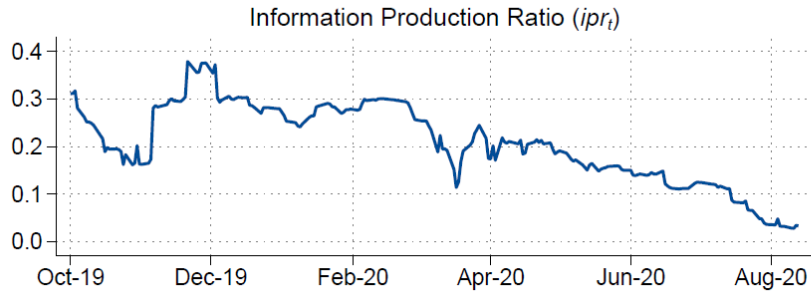
Figure 7. Information Production Ratio and Subsequent Cost of Government Interventions in Financial Institutions¹



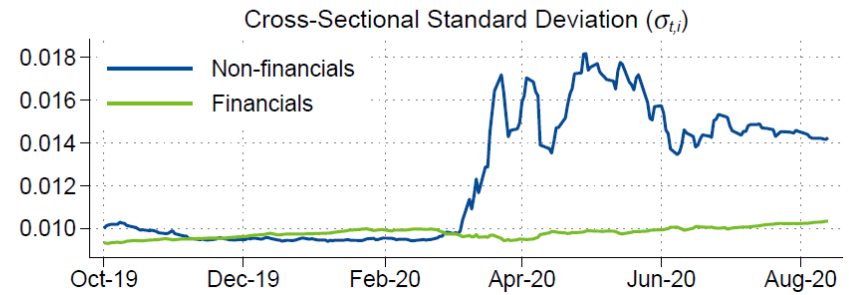
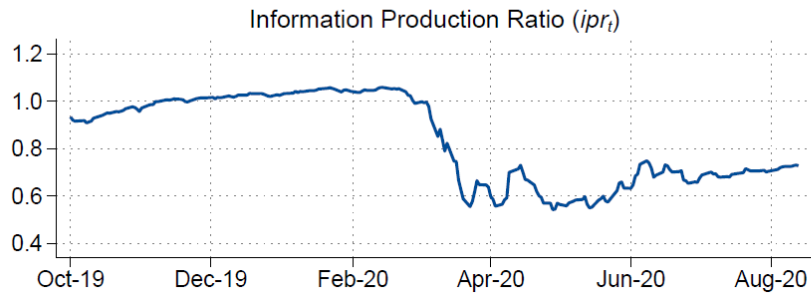
¹ Figure plots country-level ipr_{t-1} , which is lagged at an annual level, and the net cost to the government from government interventions to support financial institutions. A negative net cost is net revenues. Cost data is from Eurostat, and only “to activities undertaken to support financial institutions ... it does not include wider economic stimulus packages.”

Figure 8. Information Production Ratio During COVID-19¹

Europe



U.S.



¹ 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.

VII. TABLES

Table 1. Information Production Ratio Summary Statistics¹

| | $i pr_t$ | | | | $i pr_t^{\Delta} \times 100$ | | | |
|-----------|------------------------------------|-----------|------|-------|--|-----------|--------|--------|
| | 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 | 246.19 |
| 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 |

¹ Summary statistics for $i pr_t$ and $i pr_t^{\Delta}$ for Europe—including core Europe, periphery Europe, and the United Kingdom, and the United States. σ terms are the daily cross-sectional standard deviation of financial or nonfinancials. See section III for the calculation details. Data is daily from 2005 to 2014.

Table 2. Correlation of Region-Specific Information Production Ratio Innovations, ipr_t^Δ ¹

| | 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 |

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

¹ Daily data from 2006 through 2014.

Table 3. Cross-Sectional Variance of Changes in Financials' CDS Spreads Relative to Changes in Average Financials' CDS Spreads

| | $\Delta\sigma_{t,Financials}$ | | | | | $i\text{pr}_t^\Delta$ | | | | |
|---|-------------------------------|-------------------|-------------------|------------------|-------------------|-----------------------|-------------------|--------------------|------------------|--------------------|
| | Europe | Periphery | Core | U.K. | U.S. | Europe | Periphery | Core | U.K. | U.S. |
| $\Delta\overline{CDS}_{t,financials}^{Europe}$ | 3.24** (1.15) | | | | | 48.31** (16.41) | | | | |
| $\Delta\overline{CDS}_{t,financials}^{Periphery}$ | | 0.73*** (0.11) | | | | | 10.36** (3.72) | | | |
| $\Delta\overline{CDS}_{t,financials}^{Core}$ | | | 4.39*** (0.66) | | | | | 59.96*** (5.58) | | |
| $\Delta\overline{CDS}_{t,financials}^{UK}$ | | | | 0.63** (0.20) | | | | | 13.63 (10.53) | |
| $\Delta\overline{CDS}_{t,financials}^{US}$ | | | | | 2.22*** (0.08) | | | | | 31.99*** (2.38) |
| 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 4. Correlation with Cyclical Measures¹

| | (1) $R^{S\&P\ Europe}$ | (2) $R^{FTSE100}$ | (3) $R^{S\&P500}$ | (4) $R^{Euro\ banks}$ | (5) $R^{UK\ banks}$ | (6) $R^{US\ banks}$ |
|-----------------------|---------------------------|----------------------|----------------------|--------------------------|------------------------|------------------------|
| $i\text{pr}_t^\Delta$ | 0.00 (0.00) | 0.00 (0.00) | -0.01 (0.01) | 0.01* (0.01) | 0.00 (0.01) | -0.01 (0.02) |
| Observations | 2,252 | 2,252 | 2,252 | 2,252 | 2,252 | 2,252 |
| R^2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| | (1) $\Delta(\text{Euro VIX})$ | (2) $\Delta(\text{Spain-Bund})$ | (3) $\Delta(\text{Fin. Conditions})$ | (4) $\Delta(\text{3m EUR Libor-EONIA})$ | (5) $\Delta(\text{3m EUR Libor-OIS})$ |
|-----------------------|----------------------------------|------------------------------------|---|--|--|
| $i\text{pr}_t^\Delta$ | -0.66 (0.44) | -0.03 (0.02) | 0.04 (0.07) | 0.07 (0.05) | -0.00 (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

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

¹ Regression run on daily data from 2006 through 2014. $\Delta(\text{Euro VIX})$ is change the Euro Stoxx 50 implied volatility; $\Delta(\text{Spain-Bund})$ is the change in the spread between 10 year Spanish and German bonds; $\Delta(\text{Fin. Conditions})$ is the change in the Bloomberg Euro-zone Financial Conditions; $\Delta(\text{3m EUR Libor-EONIA})$ is the change in the slope of the 3-month/overnight spread; $\Delta(\text{3m EUR Libor-OIS})$ 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.

Table 5. Information Production Event Study: Stress Tests¹

| 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 6. Information Production Event Study: Other Event Types¹

| | 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 |

1

Table 7. Average Abnormal Information Production by Event¹

| | 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 | -0.9 | 0.2 | -1.3 | -1.5** | -0.7* | -0.8* |
| 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 |

¹ $ipr_t^A = \alpha + \beta \mathbb{I}(Event_t) + \theta_t + \varepsilon_t$ where $\mathbb{I}(Event_t)$ 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 of the events. We run the test separately for each region: Europe, core Europe, periphery Europe, the United Kingdom, and the United States. Include events are those listed in Table 5 and Table 6. OMO is open-market operations. Significance calculated using robust standard errors clustered by year where * p<0.10, ** p<0.05, *** p<0.01.

Table 8. LASSO Selection of Reference Securities¹

| Pre-Crisis | | | Global Financial Crisis | | | European Sovereign Crisis | | |
|------------|---------------------|--------|-------------------------|--------------------------|--------|---------------------------|------------------------|--------|
| Step | Vars Added | R^2 | Step | Vars Added | R^2 | Step | Vars Added | R^2 |
| 1 | iTraxx 5y | 0.0015 | 1 | iTraxx 5y | 0.0056 | 1 | iTraxx 5y | 0.0113 |
| 2 | PSI | 0.0050 | 2 | S&P Europe Property | 0.0307 | 2 | Ireland Sov Bonds, PSI | 0.0612 |
| 3 | ISEQ | 0.0061 | 3 | PSI | 0.0315 | 3 | iBoxx BBB | 0.0633 |
| 4 | S&P Europe Property | 0.0094 | 4 | Bunds, DAX, iBoxx BBB | 0.0327 | 4 | IBEX | 0.0670 |
| 5 | ASE | 0.0107 | 5 | iBoxx AAA | 0.0363 | 5 | Spanish Sov Bonds | 0.0698 |
| | | | 6 | ISEQ, remove PSI | 0.0375 | 6 | Bunds | 0.0718 |
| | | | 7 | remove S&P Property | 0.0383 | 7 | ASE | 0.0751 |
| | | | 8 | EURUSD, Greece Sov Bonds | 0.0393 | 8 | ISEQ | 0.0766 |
| | | | | | | 9 | iBoxx AAA | 0.0786 |
| | | | | | | 10 | EURUSD | 0.0800 |

¹ Table 8 presents the LASSO-selected reference securities to best explain the panel of firm-specific daily CDS returns for European financial companies, where CDS returns are calculating using equation 11. Each row shows the added variables: i.e., row 3 presents the results from a regression with the variables included in rows 1, 2, and 3, as well as a constant. LASSO estimated separately 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) which best explain the cross-section of European bank CDS returns. All reference securities are in euro-denominated return terms. Bunds is the Bloomberg 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 index for the respective country; iTraxx is the European iTraxx five-year CDS index, a portfolio of liquid CDS contracts.

Table 9. Information Production Ratio and Subsequent Cost of Government Interventions in Financial Institutions¹

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------|----------------|-------------------|-------------------|-------------------|-------------------|
| $i\text{pr}_{t-1}$ | 1.61 (1.01) | -0.30 (0.27) | -0.30 (0.27) | -0.28 (0.24) | -0.47 (0.30) |
| $i\text{pr}_{t-1}^2$ | | 1.27*** (0.41) | 1.26*** (0.42) | 1.23*** (0.42) | 1.41*** (0.44) |
| I(Periphery) | | | 0.16 (0.24) | 0.18 (0.25) | 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

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

¹ $\text{Cost}/\text{GDP}_{i,t} = \alpha + \beta_1 i\text{pr}_{i,t-1} + \beta_2 i\text{pr}_{i,t-1}^2 + \varepsilon_{i,t}$ where i denotes the country and t is year. Independent variable is the centered and lagged information production rate for country i . $\text{Cost}/\text{GDP}_{i,t}$ 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." 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.

Table 10. Information Production Ratio and Bank Outcomes¹

| | (1) | (2) | (3) | (4) |
|-------------------------------|--------------------------------|------------------------------------|-------------------------------|-------------------------------------|
| | $\Delta \ln(\text{Funding})_t$ | $\Delta \ln(\text{Gross Loans})_t$ | $\Delta \ln(\text{Assets})_t$ | $\Delta \ln(\text{Total Equity})_t$ |
| <i>Information Production</i> | | | | |
| i_{pr}_{t-1} | -1.22*** (0.28) | -1.16*** (0.28) | -1.32*** (0.28) | -1.32*** (0.41) |
| <i>Bank Characteristics</i> | | | | |
| $\ln(\text{Assets})_{t-1}$ | -0.09*** (0.01) | -0.09*** (0.01) | -0.09*** (0.01) | -0.12*** (0.01) |
| Equity/Assets $_{t-1}$ | -0.04 (0.13) | -0.49*** (0.14) | -0.25** (0.12) | -1.17*** (0.15) |
| ROAE $_{t-1}$ | 0.00*** (0.00) | 0.00*** (0.00) | 0.00*** (0.00) | 0.00*** (0.00) |
| Provisions/PPOP $_{t-1}$ | 0.00 (0.00) | -0.00** (0.00) | 0.00 (0.00) | 0.00 (0.00) |
| Income/Assets $_{t-1}$ | 0.81 (0.54) | 1.17** (0.59) | 0.91** (0.43) | 0.66 (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

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

¹ We use Fitch bank balance sheet and clean it up as follows: we limit the sample to euro area countries with semiannual reporting, per IFRS, on consolidated basis, excluding central banks, state and government banks, and supranational banks. We retain only the 500 largest banks based on their asset rank in the first half of 2007. Additionally, we 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 period, 6 months since the data is semiannual) are i_{pr} , 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 percent 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.